A COMPARISON OF TWO PROCEDURES FOR PEER GROUP ASSIGNMENT OF INSTITUTIONS OF HIGHER EDUCATION

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(ABSTRACT)

The exchange of institutional information for the purpose of comparative analysis is an established practice in the decision-making and planning processes of institutions of higher education. For comparative analysis to be meaningful, the institutions must be sufficiently alike to be comparable. Hence, colleges and universities are placed into peer groups, comprised of institutions categorized on the basis of relevant criteria. Comparative analyses and the decisions resulting from the analyses are only as good as the peer groupings that provide the sources for comparison. Thus, the way in which peer groups are formed is a cornerstone of the comparative analysis process.

The purpose of this study was to compare two grouping procedures, focal proximity and cluster analysis, in forming institutional peer groups in higher education. The two procedures were examined in terms of their relative reliability, determined by the stability of group membership over a five-year period of time, and in terms of their comparability at a single point in time, measured by the degree of agreement between peer groups formed in 1983 by each of the two procedures. Discriminant analysis was used

to examine the relative importance of the variables used as criteria in the grouping procedures.

Both procedures were found to form peer groups with greater than chance stability over the five year period of time. For one sample of institutions, focal proximity was found to be more reliable than cluster analysis in assigning institutions to peer groups. There was no difference between the two methods for a second sample of institutions. For both samples of institutions, agreement between groups formed by focal proximity analysis in 1983 and those formed by cluster analysis at the same point in time was greater than could be expected by chance. The variables that loaded most highly on the first discriminant function of the total canonical structure were PHD (proportion of degrees at the doctoral level) and LRES (research expenditures). The variables that were most important when holding all other variables constant were BA (proportion of degrees at the bachelor level) and MA (proportion of degrees at the master's level.

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TABLE OF CONTENTS

LIST OF TABLES

CHAPTER ONE

The exchange of institutional information for the purpose of comparative analysis is an established practice in the decision-making and planning processes of institutions of higher education. For instance, a university may compare faculty salaries with those of comparable universities to determine if its salaries are competitive. Similar comparisons are made by the agencies that fund universities. "Sometimes these comparisons strongly influence important decisions; sometimes they amount to little more than rhetorical gestures. But the trend is toward the former--and toward more comparisons" (Brinkman & Krakower, 1983, p. 1).

Comparative studies help provide administrators and planners with a context for decision making.

> As individuals, we exist in a social context; we understand our abilities and our history in comparison to others, and, at least to some extent, we shape our future based on that context. Institutions do the same. Whether as independent colleges or statewide systems, each tries to fulfill its particular mission. But each exists in a context of competition for faculty, students, and resources (Dunn, 1987 p. 49).

Such a context is critical for decisions regarding resource allocation. Within this context, colleges and systems need to make the best possible use of their increasingly limited resources. Following a time of plentiful resources during the sixties, the seventies and eighties have been decades of relatively limited resources, the allocation of which is based increasingly on performance measures and accountability. In the absence of absolute standards for measuring ideal resource use or many of the other concerns of higher education, administrators and planners often utilize comparative data as the standard against which to measure effectiveness and efficiency (Lawrence, Weathersby, Curry, & Eden, 1971).

Comparative studies can support all stages of the planning process. In the initial stages, comparative studies can provide reference points, or benchmarks, regarding an institution's current position. Long range planning relies on projections and estimates, which can be made on the basis of comparative analysis. In setting policy, comparative analysis can provide a basis for foreseeing "with good accuracy what would be the results of various alternative policies" (Brinkman & Krakower, 1983, p. 26). Further, comparative analysis provides the backdrop against which progress toward goals can be measured.

For comparative analysis to be meaningful, the institutions must be sufficiently alike to be comparable (Rawson, Hoyt & Teeter, 1981). Hence, colleges and universities are placed into peer groups, comprised of institutions categorized on the basis of relevant criteria. The way in which peer groups are formed is "critical to the success or failure of interinstitutional comparisons" (Brinkman & Teeter, 1983, p. 1). Failure to correctly recognize peer group members can lead to "incorrect assumptions and subsequent erroneous decisions" (Moden & Schrader, 1982, p. 1). Thus, the way in which peer groups are formed is a cornerstone of the comparative analysis process.

Statement of the Problem

Although the focus for this study is stability of peer groups, there are at least three important qualities for appropriate peer groups in higher education: homogeneity, relevance, and stability.

First, the group should be homogenous, comprised of institutions similar to each other in regard to the criteria used to form the peer group. Peers provide viable models only if they operate in environments with similar constraints and resources.

Second, the peer group should be relevant to the purpose(s) for which it will be utilized. This relevance is a function of the appropriateness of the criteria used to form the peer group. A peer group appropriate for making decisions about university athletics may not be appropriate for decisions related to faculty salaries.

Third, a peer group should be stable, with few institutions moving in and out of the group over time. This stability is most critical in the planning process, where the assumption is made that decisions made on the basis of peer data will have long term consequences and are part of an institutional shaping process. Planning encompasses the management of institutional change across time. It follows that, if peers are to be a valid context for decision making, there must be a reasonable expectation that the peers will remain peers at least for the period of time involved in a particular planning endeavor--often five years.

Stability provides a context to measure a pattern of relative standing through longitudinal studies or trend analysis (Makowski & Wulfsberg, 1980). Also, measures across time provide a yardstick for assessing both progress toward goals and the continued appropriateness of those goals.

Stability is also important in enhancing credibility with funding agencies. An institution that justifies requests on the basis of a number of different peer groups may appear to be opportunistic. In addition to providing credibility, stability may reduce problems due to incomparable data. Data elements are not always identically defined or reported across institutions and higher education systems. Development of a single, stable set of peers permits efforts to establish uniform data definitions and reporting practices to focus on a relatively small group of institutions (Whiteley & Stage, 1987).

Stability of peer groups is certainly a function of the dynamics of change operating in the institutions that make up peer groups. A major change in mission would be expected to result in a sufficient shifting in the pattern of change of an institution to make an historical peer group no longer appropriate.

Stability is also a function of the reliability of the procedures used to form peer groups. At this point, clarification of the use of the terms stability and reliability is in order. Stability refers to the stability of peer groups; a state of having few institutions move in and out of a group over time. Reliability refers to the reliability of a statistical procedure or process. In this context, reliability is defined as a procedure's ability to replicate peer group assignment of colleges and universities at different points in time.

The stability of peer groups is dependent upon the reliability of the procedures used to create them. The more reliable a procedure is, the more stable the peer groups it creates will potentially be. Although there have been a few studies that have compared the agreement between groups formed by different procedures at a point in time (Teeter & Christal, 1987; Makowski & Wulfsberg, 1980), there have been no studies examining the agreement between groups formed by a particular method at different points in time.

Purpose of the Study

The purpose of this study was to compare two grouping procedures, focal proximity and cluster analysis, in forming institutional peer groups in higher education. The two procedures were examined in terms of their relative reliability, determined by the stability of group membership over a five-year period of time, and in terms of their comparability at a single point in time, measured by the degree of agreement between peer groups formed in 1983 by each of the two procedures.

Research Questions

The main research questions for this study were as follows:

1. Do each of the two procedures produce groups which remain relatively stable over a five year period of time?
2. Is there a difference between methods in the stability of the groups produced?
3. Are the two procedures equivalent in terms of the peer groups they produce?
4. Which variables contribute most in determining institutional assignment to peer groups?

Need for the Study

Institutions of higher education make decisions based on comparative analysis. Comparative analysis is also used by funding sources and governmental agencies to make decisions about institutions of higher education. These comparisons, and hence the decisions, are only as good as the peer groupings that provide the sources for comparison. The reliability of the procedures for developing peer groups remains untested, hence the peer groups themselves are unproven bases for comparative analysis conducted for the purpose of strategic planning.

This study will provide indices of the reliability of two approaches to peer group formation as a function of the stability across time and the consistency at a point in time of the groups they form. These indices will provide critical information regarding the efficacy of peer groups formed by these procedures to those responsible for selecting institutional peers and to those who use peers as the basis for comparative analysis and strategic planning. The study will also present a methodology for measuring the stability of peer groups across time.

Definition of Terms

Comparative Data: Data gathered from similar institutions of higher education for the purpose of institutional comparisons.

Comparative Analysis: The use of comparative data for the purpose of institutional comparisons.

Peer Institution: An institution of higher education that is similar to a given institution or institutions in regard to one or more selected characteristics.

Peer Group: A set of institutions of higher education that are categorized on the basis of similarity to one another in regard to one or more selected characteristics.

Stability of a Peer Group: A state of having few institutions moving in or out of a peer group over time.

<u>Reliability of a statistical grouping procedure:</u> A procedure's ability to replicate peer group assignment of colleges and universities at different points in time.

Delimitations

The delimitations of the study are as follows:

1. The criteria for forming peer groups are those that would create groups appropriate for faculty salary comparisons.
2. Reliability of the procedures for categorizing institutions will be measured in terms of the agreement between groups formed according to 1983 data and those formed according to 1978 data.
3. The population of institutions to be grouped consists of all colleges and universities categorized as major doctoral granting institutions or comprehensive institutions according to the National Center for Higher Education Systems (NCHEMS) taxonomy.
4. Only two statistical procedures for creating peer groups are compared: cluster analysis and focal proximity analysis.
5. The study focuses on the **methodologies** used to form peer groups. It should be understood that following the use of any statistical procedure, judgment must

be used in making final decisions. "Analyses of numbers are not a substitute for good judgment, but rather should enhance and inform judgment" (Teeter & Christal, 1987, p. 13).

Limitations

The limitations of the study are as follows:

1. Although a measure of the cost of living might be worthy of consideration in the selection of appropriate salary peers, such a measure was not included as a criterion for group assignment in this study. If actual salary comparisons were the intended outcome of a peer selection process, consideration of including such a measure would be reasonable.
2. There are conditions in higher education that can affect the stability of peer groups that have nothing to do with the reliability of the procedure used to create them. An example of one of these conditions would be a change in mission for one or more members of a peer group.
3. The sources of data used for the generation of peer groups were the 1983 and 1978 Higher Education General Information Surveys (HEGIS) collected by the National Center for Educational Statistics (NCES).

Although institutions generally report accurate data to NCES, differences in institutional and state practices may result in data that are not totally comparable (Christal, 1983). Problems in the comparability of HEGIS data include differences in reporting practices, differences in institutional funding practices, and different data element definitions (Lapovsky, 1983).

Despite the problems associated with the HEGIS data, HEGIS is the only source of universally collected higher education data currently available. Studies conducted by Christal and Firnberg (1983), Brown, Padget, and Embry (1980), and Andrew, Fortune and McCluskey (1981) concluded that HEGIS is an important source of higher education data and should be used for institutional comparisons.

CHAPTER TWO

Literature Review

Introduction

Several areas in the literature may be identified as appropriate for discussion and review: 1) comparative analysis, 2) institutional classification and comparison groups, 3) criteria used to form institutional peer groups, 4) methodologies for producing institutional peer groups, and 5) measures of agreement. The majority of the information needed to cover these topics was found in the literature on higher education. Adequate coverage of the last two areas, methodologies for producing peer groups and measures of agreement, required a review of more general statistical literature.

Comparative Analysis

Comparative analysis is employed at all levels of management in higher education to guide and direct changes in American colleges and universities (Whiteley & Stage, 1987). At each level of management, comparative analysis is used for a variety of purposes. "Comparative judgments are the basis of virtually all we do in measuring, assessing, and evaluating educational resources, processes, and outcomes" (Fincher, 1985, p. 108).

The trend over the past decade has been toward increased use of interinstitutional comparisons at the state level (Brinkman, 1987). Higher education state or system boards exist in every state (McCoy, 1987), and their use of interinstitutional comparisons has become commonplace (Brinkman, 1987).

Financial comparisons are the most common interinstitutional comparison made at the state or system level. "For institutions in the public sector this is serious business, since more often than not some aspect of financial support, typically for either faculty salaries or overall funding, will depend in part on the outcomes of these comparative analyses" (Brinkman, 1987, p. 105).

The responsibility of managing higher education at a time when resources are limited requires planners at the state level to determine how effectively colleges and universities are managing their resources and to determine reasonable resource allocations for specific activities (Lawrence, et al., 1971). "Interinstitutional comparisons provide an important metric for determining relative levels of support, institutional needs, productivity and performance" (McCoy, 1987, p. 74).

Even at the institutional level, part of the motivation for using peer comparisons comes from the emphasis on comparative analysis at the state and system level.

Institutional administrators frequently become data suppliers in order to satisfy the growing demand for comparative data of external agencies at the state or federal level (Whiteley & Stage, 1987). The data are often used for the purposes of justifying resource requests and demonstrating productivity. Since these data are the basis of decision making by external agencies, an increased reliance on peer comparisons is fostered at the institutional level for administrators involved in the internal decision-making process (Whiteley & Stage, 1987).

At the institutional level, as well as the state level, comparative analysis is a powerful tool in the planning process (Brinkman & Krakower, 1983; Whiteley & Stage, 1987; Rawson, et al., 1981). At this level, there are many areas of decision making which draw upon comparative analysis. The most frequently cited specific uses of comparative analysis include indexing faculty and administrator salaries (Whiteley & Stage, 1987; Teeter, 1983; Teeter & Brinkman, 1987; Rawson, et al., 1981; Brinkman & Teeter, 1987; Cliff, 1978; Brinkman & Krakower, 1983); guiding judgments about internal budget allocations and finances (Whiteley & Stage, 1987; Teeter, 1983; Rawson, et al., 1981; Christal & Wittstruck, 1987); indexing tuition and fees (Teeter & Brinkman, 1987; Christal & Wittstruck, 1987); guiding decisions about institutional structure (Brinkman & Teeter, 1987; Whiteley & Stage, 1987); evaluating programs (Teeter, 1983; Lawrence, et al., 1971); determining faculty size and work load (Lawrence, et al., 1971; Teeter & Brinkman, 1987; Christal & Wittstruck, 1987); monitoring enrollment trends (Teeter, 1983; Christal & Wittstruck, 1987); evaluating tenure policies (Teeter, 1983); allocating space (Whiteley & Stage, 1987); and monitoring degrees awarded (Christal & Wittstruck, 1987).

In a study conducted by Andrew, Fortune and McCluskey (1981) to determine who were users of HEGIS data and for what purposes, the following types of data, in the given order, were found to be most often used for making interinstitutional comparisons: faculty salaries, enrollment by discipline, degrees awarded by discipline, enrollment by sex, degrees awarded by level, enrollment by race, financial status, degrees awarded by race, residence and migration of students, degrees awarded by sex, and classified-employee salaries.

Due to the applied nature of interinstitutional comparisons, the literature is not rich in reports of actual comparisons in higher education. However, a few such reports are available. For studies involving comparisons of a single institution with its peers, the majority of reported comparisons were financial in nature.

A comparison of the University of Maryland with peer institutions was conducted to compare faculty salaries, administrative salaries, expenditures per student for libraries, total revenues and expenditures, expenditures by program, revenues by source and part-time/full-time enrollment ratio (Maryland State Board for Higher Education, 1983). Financial expenditures at the University of North Carolina, Chapel Hill were compared to other public universities in the Association of American Universities (AAU) Data Exchange Group (Sandford & Sadler, 1984). The salary schedule and the allocation of salary funds at California State University were compared to those at comparison institutions for the purpose of determining problem areas in California State's salary structure (California State Postsecondary Education Commission, 1985).

Athletic funding and athletic staff salaries at Montana State University were compared to similar programs at peer institutions to determine if their funding levels were similar (Fullerton, 1985). Financial information at Indiana University Libraries was compared to peer institutions for the purpose of rationalization of budget allocation procedures (Bentley, 1985).

An institutional study that did not involve financial concerns was conducted at the University of Hawaii. This study compared faculty perceptions at the University of

Hawaii with faculty perceptions at peer institutions to determine how well faculty perceived their institutions to be functioning (Chaille, 1983).

State and system level comparisons have also been primarily concerned with financial issues. The California State Postsecondary Education Commission (1983, 1984, 1985) has published annual results of salary and fringe benefits comparisons between California postsecondary institutions and their peer institutions. The impetus for these annual reports stemmed from state legislation which requested that salaries and fringe benefits be studied "in order that such California institutions of higher education may be able to compete for the talent necessary to provide the highest quality of education..." (California State Postsecondary Education Commission, 1985, p. 3). The studies include trend analyses over various periods of time.

Interinstitutional comparisons were conducted as part of an evaluation of the Missouri master plan for education. Comparisons included the distribution of revenues and expenditures per student over a number of categories and on a number of program characteristics by level and discipline (Missouri State Coordinating Board for Higher Education, 1984).

Three studies were reported which compared Maryland public colleges and universities with other institutions.

In the first study (Allard, 1982), faculty salaries, rank and tenure were compared to those at selected peer institutions at two points in time--academic years 1976-77 and 1981-82. The second study (McKeown, 1982) compared tuition and fee charges and policies with those of other states. The findings of the study included the fact that "twenty-two states have tuition policies that relate tuition to the cost of education, to benchmark or peer institutions or states, or to variables exogenous to higher education..." (McKeown, 1982, p. 1). The third Maryland study compared policies governing external and off-load employment of faculty in Maryland institutions with policies at peer institutions (Allard, 1982).

Institutional Classifications and Comparison Groups

The earliest classifications of institutions were designed to provide organization for national reporting purposes. Among the first of these classification systems was that of the National Center for Educational Statistics (NCES), now known as the Center for Educational Statistics (CES). In its early typology, NCES classified institutions into one of three categories: Universities, Other Four-Year Institutions, or Two-Year Institutions (Makowski, 1981). The NCES system was very simple and fairly stable over time, but tended to conceal major differences among institutions.

There also were no objective criteria for classifying institutions in this system (Makowski & Wulfsberg, 1980). The CES is currently revising its classification system.

In 1970, the Carnegie Commission on Higher Education developed a classification system. This system was updated in 1976 and again in 1987 (Teeter & Brinkman, 1987). The Carnegie Commission improved upon earlier approaches by basing classification on several objective characteristics of an institution, including degrees and academic programs offered, federal support for research, size, and test scores of students at admission or proportion of undergraduate students entering graduate study (Terenzini, Hartmark, Lorang, & Shirley, 1980). The general categories in the Carnegie Commission typology are: Doctoral-Granting Institutions, Comprehensive Universities and Colleges, Liberal Arts Colleges, Two-Year Colleges and Institutes, and Professional Schools and Other Specialized Institutions (Smart, 1978).

To further improve classification of institutions in higher education, the National Center for Higher Education Management Systems (NCHEMS) initiated work on a new classification system in 1977 (Makowski & Wulfsberg, 1980). Three objective criteria were used to classify institutions: the number of degrees awarded by degree level, the number of programs in which degrees were awarded, and the ratio of degrees awarded by program (for specifically selected programs) to total degrees awarded (Makowski & Wulfsberg, 1980). The NCHEMS taxonomy defines five major categories: Major Doctoral-Granting Institutions, Comprehensive Institutions, General Baccalaureate Institutions, Professional and Specialized Institutions, and Two-Year Institutions.

Broad classifications such as those described are sometimes used for the purpose of comparative analysis. There are advantages in using these classifications as comparison groups--a lot of work has already been expended in developing the categories and the groups have already established credibility (Teeter & Brinkman, 1987). However, "it should never be assumed that this type of group is a reasonable choice" as a comparison group (Brinkman & Teeter, 1987, p. 8). The problem with using these classifications for comparative analysis is that there is too much within group diversity. In many aspects, there may be as much variation within groups as between (Korb, 1982). In most cases more institutional similarity is needed for meaningful comparisons.

Brinkman and Krakower (1983) identified four types of comparison groups: jurisdictional, competitor, aspiration, and peer. A jurisdictional group is used when the rationale for conducting the comparison is that all of the institutions are in a common jurisdiction, such as programs within an institution or institutions within a state or system.

A competitor group is used when the rationale for the comparison is to evaluate competitive standing within the educational arena. Usually these comparisons are at the institutional level. The institutions in both competitor and jurisdictional groups may be quite dissimilar from each other in some respects.

An aspiration group is made up of institutions that have one or more characteristics that the comparing institution is considering emulating. The aspiration group may be made up of institutions with higher faculty salaries, higher tuition charges, or some other characteristic viewed by the comparing institution as desirable.

The fourth type of comparison group, the peer group, is comprised of institutions which are similar in regard to "contextual factors important to a particular analysis, if not more generally. Their overall similarity allows comparative data, say on resource allocation, to yield a certain amount of meaning that they otherwise would not have" (Brinkman & Krakower, 1983, p.15). Of all types of comparative analysis, peer group analysis is the most difficult to do correctly (Brinkman & Krakower, 1983).

Brinkman and Teeter (1987) reiterate definitions of peer, competitor, and aspiration groups, but place jurisdictional groups in a larger set which they label predetermined groups. Four types of predetermined comparison groups are identified: natural, traditional, jurisdictional, and classification based. Membership in natural groups is based on some common concern or connection, for example membership in an athletic conference or a regional compact, location in a particular region, membership in an association of higher education institutions, or membership in a consortium. Though group membership based on these natural associations may imply that the institutions have certain commonalities, whether the group is a valid basis for comparative analysis will depend upon the nature of the comparison (Brinkman & Teeter, 1987).

A traditional comparison group is simply one that has been used for a long time. However, the group may or may not be an appropriate comparison group.

Jurisdictional groups are more narrowly defined to include institutions that are part of the same political or legal jurisdiction. Comparisons within jurisdictional boundaries are generally motivated by the responsibility that elected officials and state agency staff have for the institutions within their domain. The reasonableness of these comparisons is, again, dependent upon the nature of the comparison.

The fourth predetermined comparison group is one based on an institutional classification designed for national reporting. The problems and advantages of this type of group were discussed earlier.

Criteria Used to Form Peer Groups

There are many variables that have been used as criteria for peer group formation. As noted earlier in this document, the relevance of a peer group is a function of the criteria used to create it, therefore the selection of appropriate variables upon which to base a peer group is quite important.

In order to create a "general-purpose" peer group, it is probably best to select variables that reflect institutional mission and environment (Brinkman & Krakower, 1983). In creating a peer group for any purpose, it is important not to include variables that reflect the comparison issues. For instance, since most institutional comparisons concern resource utilization or allocation, these dimensions probably should not be criteria for developing a peer group. If the criteria for group formation and the issues of comparison are the same, a "self-defeating circularity will be built into the analysis" (Brinkman & Krakower, 1983, p. 46).

Criteria which have commonly been used to create institutional peer groups in higher education include: number of degrees earned by level of degree (Makowski & Wulfsberg, 1980; Teeter & Christal, 1987), percentage of students in particular programs (Teeter & Christal, 1987; Makowski & Wulfsberg, 1980), number of fields in which degrees are granted (Makowski & Wulfsberg, 1980), research expenditures (Teeter & Christal, 1987; Korb, 1982; Terenzini, et al., 1980), number or type of faculty (Moden & Schrader, 1982; Terenzini, et al., 1980) number of students (Moden & Schrader, 1982; Teeter & Christal, 1987), size of facilities (Korb, 1982; McCoy & Halstead, 1984; Terenzini, et al., 1980), faculty salary (Terenzini, et al., 1980; McCoy & Halstead, 1984), and part-time/full-time student ratio (Teeter & Christal, 1987).

Variables which are sometimes used to narrow the population of institutions from which peers will be selected include: control (public/private), landgrant status, presence of a medical (or other professional) school, and location (urban/rural) (Teeter & Christal, 1987).

Methodologies for Producing Peer Groups

A number of statistical procedures have been used in the formation of peer groups. Sectoring was one of the earliest methods developed. This method divides institutions into groups through their possession or lack of possession of an attribute. This method is limited to use with dichotomous, nominal variables and will rarely produce a peer group (Brinkman & Krakower, 1983). A somewhat more widely applicable method is the threshold method, often used in conjunction with the sectoring method to allow the inclusion of both continuous and nominal variables. The threshold method assigns an institution to a group based on where the institution lies on an interval scale. For instance, if research endowments are $20,000 or more per year, the institution is in a particular peer group; if endowments are less than $20,000, it is in another group.

General classification systems which use the threshold method are the Carnegie Commission on Higher Education taxonomy (Terenzini, et al., 1980), the NCHEMS taxonomy (Teeter & Brinkman, 1987) and the NCES classification system (Brinkman & Krakower, 1983). Makowski and Wulfsberg (1980) compared the Carnegie Commission, NCHEMS, and NCES classification systems on the basis of the homogeneity of the groups produced by each system. They found the NCHEMS system to be superior at most levels of classification and for most variables. NCHEMS has more recently developed a modified threshold system for identifying peer groups for individual institutions. This procedure combines thresholds and a simple statistical algorithm (Teeter & Christal, 1987).

There are several limitations to the threshold method. One limitation is the arbitrariness of the cutoff points (Terenzini, et al., 1980; Brinkman & Krakower, 1983). Also, very small differences in data can result in very different decisions--with a $20,000 cutoff point, an institution with $20,001 might be excluded from a peer grouping, while an institution with $20,000 is included.

An attribute that can be both a weakness and a strength of this method is the transparency of the procedure (Teeter & Brinkman, 1987). Due to the simplicity of the procedure, it is easily understood by non-researchers, but due to the same simplicity, it can be easily manipulated to produce politically motivated groups.

A third approach to grouping institutions in higher education is the hybrid approach. This approach combines a strong emphasis on data and statistical algorithms with an emphasis on input from administrators (Teeter & Brinkman, 1987). For instance, the Kansas Board of Regents is using a hybrid method to identify peer groups for the six four-year institutions in Kansas (Teeter & Brinkman, 1987). This procedure initially identifies peer states; identifies appropriate four-year, public institutions within those states; and divides these institutions into three groups according to the number of Ph.D. programs offered and the size of the city in which each institutions is located.

Each of these three groups corresponds to a group of the similarly divided Kansas institutions.

At this point, college administrators review the lists of institutions and remove from consideration any institution whose curriculum is too narrow. For the remaining institutions, the raw data on enrollments, finances, and degrees awarded is converted into z-scores, which are used to calculate comparison scores for each institution. The comparison scores are standardized and weighted and are summed to produce a similarity score. The institutions are then rank ordered for each Kansas institution on the basis of their similarity scores.

Teeter and Christal (1987) compared the NCHEMS peer group methodology to the Kansas hybrid methodology using the University of Kansas (KU) as the target institution, or the institution for which a peer group would be formed. In one iteration of the study, seven out of the ten top-ranked peer institutions produced as peers for KU by the two methods were the same. In a second iteration, using slightly different criteria, eight of the top ten institutions were the same.

The study identified strengths and weakness for each of the methods. Strengths identified for the NCHEMS method were that it is easily understood by non-statisticians, easy to implement, and is inexpensive to use. Weaknesses were the arbitrariness of the methodology and a lack of qualitative measures.

Strengths of the Kansas method were its statistically sound methodology and the fact that it is also inexpensive to use. Weaknesses were the difficulty non-statisticians would have in understanding the methodology and a lack of qualitative measures.

A fourth approach to grouping institutions is the proximity approach (Teeter & Brinkman, 1987). In this approach, the data are standardized and then the Euclidian distance is computed between the target institution and the candidate institutions. The institutions are then rank-ordered based on their distance from the target institution.

Euclidian distance is the generalized distance between the target institution and the candidate institutions based on measures on a number of criteria. Although the actual algorithm for Euclidian distance would likely be unfamiliar and too statistically oriented for non-statistician administrators, the concept is not difficult to grasp intuitively.

The proximity approach is also fairly simple and inexpensive to run since common computer packages for cluster analysis will output the Euclidian distance for each institution (Teeter & Brinkman, 1987). This approach is currently used by the State Council for Higher Education in

Virginia (SCHEV) to form peer groups for Virginia colleges and universities.

A fifth approach to institutional classification, spatial configuration analysis, combines factor analysis and multidimensional scaling to create peer groups. Spatial configuration is used to represent the maximum retainable variance of multiple variables in only a few dimensions so that a graph can be made in three-dimensional space (Moden & Schrader, 1982). Smart, Elton and Martin (1980) and Moden and Schrader (1982) used spatial configuration analysis with both quantitative and qualitative variables to identify peer institutions.

Several limitations of the spatial configuration approach have been identified. First, the statistical methodology is very complex and very difficult to explain to non-statisticians. Also, much of the variance accounted for by the variables selected as criteria may be lost by the dimension reduction. Finally, the method is not available in most statistical software packages.

Another method used to form groups, cluster analysis, is more commonly used to form higher education peer groups (Brinkman & Teeter, 1987). Cluster analysis is a general name for a set of algorithms that identify groups of units with similar attributes. Though cluster analysis relies primarily on statistical algorithms, judgment is required in

(1) determining which algorithm to apply to a particular application, (2) deciding where to draw group boundaries, and (3) choosing weights to assign the variables in the model.

Cluster analysis was developed specifically as a tool for comparative analysis and "seems made to order for the peer group selection problem" (Brinkman & Teeter, 1986, p. 12). However, though cluster analysis appears conceptually well suited to mapping out peer groups from a population of institutions, it is not apparent that it is well suited for determining the peer group for a target institution (Brinkman & Teeter, 1987)

The three types of clustering algorithms that are most commonly used in the social sciences are hierarchical agglomerative, iterative partitioning, and factor analytic (Aldenderfer & Blashfield, 1984). Of these, the two types found in the literature of institutional classification in higher education are hierarchical agglomerative (Terenzini, et al., 1980) and iterative partitioning (Korb, 1982). In the published studies in which cluster analysis was used for institutional peer group assignment, factor analysis was used for data reduction and discriminant analysis was used to test the "goodness of fit" of the final clusters (Terenzini, et al., 1980; Elsass & Lingenfelter, 1980; Korb, 1982).

Hierarchical agglomerative algorithms begin with the computation of a similarity or distance matrix between the units to be clustered. Probably the most common distance measure is Euclidian distance (Everitt, 1974). The methods use these measures to join those units which are most similar. The process is accomplished in stages, with units being joined at each stage until all units are members of one group.

There are several hierarchical agglomerative algorithms. These algorithms are distinguished from one another chiefly by the different rules applied for the formation of clusters. Though there are at least a dozen of these algorithms, the four most popular are single linkage, complete linkage, average group linkage, and Ward's method (Aldenderfer & Blashfield, 1984).

There are problems associated with agglomerative hierarchical clustering techniques. One problem is that they do not allow for the reassignment of units that may have been incorrectly classified at an early stage of the clustering process. A second problem is chaining--the tendency to cluster together units linked by chains of intermediates (Dillon & Goldstein, 1984). Also, these methods require a great deal of computer memory storage and thus handle a limited number of variables.

Iterative partitioning methods begin with an initial partitioning of the units into a specified number of clusters. Each unit is then assigned to the cluster with the nearest centroid--cluster mean. After each unit has been assigned to a cluster, new centroids are computed. The assignment of units to clusters and the updating of centroids based on each iteration of group assignment is continued until no more institutions change clusters (Aldenderfer & Blashfield, 1984). A common iterative partitioning algorithm, K-means clustering, provides the initial partitioning by the assignment of K (the number of clusters) seed points, or estimates of cluster means.

Unlike hierarchical methods, iterative partitioning methods do not require a great deal of memory storage and can thus handle a large number of variables. Also, since the methods make multiple passes through the data, poor assignment of units to clusters early in the procedure can be corrected at later stages. These methods also do not form chains of units (Aldenderfer & Blashfield, 1984).

The performance of several clustering algorithms has been tested empirically in a number of studies (Baker, 1974; Kuiper and Fisher, 1975; Blashfield, 1976; Milligan & Isaac, 1978; Bayne, Beauchamp, Begovich & Kane, 1979; Edelbrock, 1979; Milligan, 1980). These studies utilize Monte Carlo methods in generating data which is used to compare the ability of various algorithms to recreate true clusters under a variety of error conditions and parameterizations.

Bayne, Beauchamp, Begovich and Kane (1979) compared thirteen clustering methods for six types of parameterizations, finding the K-means partitioning method best overall. Milligan and Isaac (1978) compared the accuracy of four hierarchical algorithms using data sets that differed in degree of data perturbation. They found the average-group and Ward's methods to be superior. In similar studies, Mojena (1977), Blashfield (1976), and Kuiper and Fisher (1975) found Ward's method best overall. Kuiper and Fisher (1975) further stated that one of the more valuable uses of hierarchical clustering methods is identifying outliers in a visual manner. Outliers have been found to cause clustering methods to perform poorly (Kuiper & Fisher, 1975).

Edelbrock (1979), comparing the accuracy of several hierarchical algorithms under varying conditions of coverage, found average group linkage to have the highest accuracy. Baker (1974), comparing the stability of single and complete linkage algorithms on the basis of robustness to measurement errors, found complete linkage to be superior.

Milligan (1980) compared fifteen clustering algorithms based on six different error perturbations. In the first phase of his study, Milligan compared individual algorithms. He found that average group linkage performed better than other hierarchical procedures and that hierarchical procedures performed better than K-means procedures when random seed points were used.

In the second phase of his study, Milligan examined a combination of methods. He found the K-means algorithm using the centroids from the average group method as seed points to be best overall. This combination of methods was robust to all types of data error examined.

Measures of Agreement

A number of measures have been used to estimate the accuracy or stability of clustering methods. Gross (1972) and Bayne (1979) used the probability of missclassification to assess the accuracy of clustering algorithms. However, the measures of agreement most commonly used for comparing the accuracy of clustering algorithms are kappa, developed by Cohen (1960), and a statistic developed by Rand (1971). Rand's statistic is identical to the measure of agreement developed by Brennan and Light (1974) and is a specific case of a category of measures of agreement presented by Hubert and Levin in 1976 (Edelbrock, 1978).

These measures of agreement have been used in several studies to compare clustering algorithms. Kuiper and Fisher (1975), Mojena (1977), and Milligan (1980) used Rand's statistic to compare several clustering algorithms. Milligan and Isaac (1978) used both Rand's statistic and kappa to compare the accuracy of four hierarchical algorithms. Blashfield (1976) and Edelbrock (1979) used kappa to compare the accuracy of several algorithms.

Measures of cross-classification agreement are special cases of association (Liebetrau, 1983) and are generally linear functions of each other (Hubert & Levin, 1976). Milligan and Isaac (1978) found kappa and Rand's statistic to correlate .97 with each other. However, kappa has an advantage over other measures of being equal to zero at a chance level of agreement while other measures will produce positive, nonzero values as a function of the relative size of the underlying population (Edelbrock, 1979).

Summary

The literature clearly reveals the importance and widespread use of comparative analysis in higher education. At both the state and institutional levels, financial comparisons are the most common type of interinstitutional comparison, most often for the purposes of salary comparison or resource allocation.

Although broad classifications of institutions, designed to provide organization for national reporting, are sometimes used for the purpose of comparative analysis, it is more appropriate to use a comparison group for this purpose. Of the types of comparison groups identified, the peer group best provides the relevance and homogeniety of institutions needed to lend meaning to interinstitutional comparisons. It is also the most difficult type of comparison group to produce correctly.

The relevance of a peer group is a function of the criteria used to create it, therefore the selection of appropriate variables upon which to base a peer group is quite important. In creating a peer group for any purpose, it is important not to include variables that reflect the comparison issues, such as including faculty salaries in a model designed to create a peer group for comparing faculty salaries.

A number of statistical procedures have been used in the formation of peer groups. These procedures range from the very simple, such as sectoring and the threshold method, to the highly sophisticated, such as spatial configuration and cluster analysis. Both very simple and very complex procedures have limitations related to the politics of institutional peer group selection. Procedures such as sectoring and the threshold method are very easy for non-researchers to understand, but, due to the nature of the procedures and their transparency, can be easily manipulated to produce politically motivated groups. The more complex procedures, on the other hand, are very difficult for non-researchers to understand. They may fail to receive the acceptance of decision makers who do not understand the process and therefore do not trust the results of the grouping procedure. The proximity approach is a procedure that employs statistically sophisticated methodology and yet is conceptually simple and not difficult for non-researchers to grasp intuitively.

Some statistical procedures for forming peer groups, such as cluster analysis and spatial configuration, map out peer groups from a population of institutions by creating mutually exclusive groups of institutions. Others, such as the hybrid and the proximity approaches, form peer groups for specific, target institutions. There is no requirement that these groups be mutually exclusive. It is not apparent that a procedure designed to map out mutually exclusive groups from a population of institutions is well suited for determining the peer group for a specific insitution.

The measures of agreement most commonly used for comparing the accuracy of clustering algorithms are kappa, developed by Cohen (1960), and a statistic developed by Rand (1971). Kappa has the advantage over other measures of being equal to zero at a chance level of agreement while other measures will produce positive, nonzero values as a function of the relative size of the underlying population (Edelbrock, 1979).

CHAPTER THREE

Research Design and Methodology

The population for the study consisted of two major categories of institutions selected from the taxonomy of postsecondary institutions of the National Center for Higher Education Management Systems (NCHEMS). These categories were (1) Major doctoral granting institutions and (2) Comprehensive institutions. Initially, twenty target institutions were randomly selected from the combined institutions in these categories. A second set of twenty target institutions was then selected for the purpose of replicating the analyses.

The entire population of institutions in these categories was accessed for selecting peer groups for the target institutions. All institutions were assigned to peer groups, with the exception of outliers, which were rendered separate by their distance from established groups. In the case of groups formed by cluster analysis, clusters with fewer than ten institutions were not included in comparisons.

The data for the study were obtained from the 1983 and 1978 Higher Education General Information Surveys (HEGIS) collected by the National Center for Educational Statistics (NCES). Data elements located on the Degrees and Other Formal Awards, Fall Enrollment and Compliance Report and

Financial Statistics of Institutions of Higher Education surveys were utilized as peer-group selection criteria. The specific variables were:

1. FTE enrollment (LFTE)
2. Percent part-time enrollment (PT)
3. Percent of total degrees at the doctoral level (PHD)
4. Percent of total degrees at the masters level (MA)
5. Percent of total degrees at the bachelors level (BA)
6. Research expenditures (LRES)
7. Percentage of degrees awarded in the following disciplines:
   - Engineering/Computers/Architecture (ENG)
   - Business (BUS)
   - Education/Home Economics (EDUC)
   - Biological and Physical Sciences (SCI)
   - Fine Arts (ARTS)
   - Health and Health Related (including Veterinary Medicine) (HEALTH)
   - Humanities (HUMAN)
   - Social Sciences (SOCSCI)
   - Law (NLAW)

These variables were selected specifically for forming peer groups for faculty salary comparisons. Other variables, including faculty salary, might be selected for other purposes. The categories represented by these variables--enrollment, research emphasis, degree levels, and degrees by disciplines--are commonly cited as criteria for peer group formation. These specific variables were recently selected by the State Council of Higher Education in Virginia (SCHEV) for creating peer groups for salary comparisons in the Commonwealth of Virginia.

The log transformations of FTE enrollment and research expenditures were used to stabilize the variance for these measures. Otherwise, fluctuations in the values of these variables could have a disproportionate impact on institutions which initially had smaller values.

All variables were standardized to zero mean and unit variance. In most cases of clustering, standardization of the variables in this manner is recommended. Euclidian distance should probably not be used with raw data as it is greatly affected by variables with varying scales. Because of this problem, variables are usually standardized when using Euclidian distance (Everitt, 1974).

The cluster procedure used was a combination of two algorithms of cluster analysis. First, Ward's method, a hierarchical algorithm, was used to identify initial clusters. Then the centroids of the clusters thus identified were used as "seed points", or initial estimates of cluster centers, for a K-mean clustering algorithm. A multi-method approach to cluster analysis such as this has been demonstrated to be superior overall in regard to robustness to error (Milligan, 1980). The Ward's clusters were formed using PROC CLUSTER in SAS (SAS Institute Inc., 1985). The K-means clusters were formed using PROC FASTCLUS (SAS Institute Inc., 1985).

The focal proximity procedure was designed to form peer groups for specific (target) institutions. This procedure produced a rank ordering of the institutions most similar to each target institution based on the Euclidian distance between institutions. The size of peer groups was determined by the researcher, who decided the cutoff point in the rank ordered list. In this study, the Euclidian distance between institutions was computed using PROC FASTCLUS (SAS Institute Inc., 1985)

For purposes of comparing the groups formed by each procedure at a point in time, the size of the peer groups was based on the size of the peer group containing each target institution in the cluster analysis. For instance, if a particular target institution was assigned to a group containing 30 institutions by the cluster procedure, then the first 29 institutions on the rank ordered list were assigned to it to form a peer group of 30 institutions for the focal proximity analysis. This matching of group size made it possible to directly compare the groups formed by the two methods.

The measure of agreement used to determine agreement between groups formed by different procedures and at different points at time in this study is kappa (Cohen, 1960).

Kappa is based on two quantities:

p_o = The proportion of observed agreements between groups

p_c = The proportion of agreements expected by chance

The coefficient kappa is the proportion of agreement between groups after removing the agreement that can be attributed to chance (Cohen, 1960) and is defined as follows:

$$k = (p_o - p_c) / (1 - p_c)$$

Stability of Peer Groups Across Time

The relative reliability of the procedures was a function of the stability over time--between 1983 and 1978--of the peer groups formed by each method. This stability was measured on the basis of agreement between peer groups formed using 1983 data and those formed using 1978 data by each of the two methods. For the focal proximity analysis, kappa was computed between the group formed for each target institution in 1983 and the group formed for that institution in 1978, resulting in 20 kappa values (one for each target institution) for each of the two samples. These kappa values were then averaged, resulting in one kappa value for each sample.

For the cluster analysis, kappa was similarly computed in reference to target institutions. Kappa was computed between the cluster which contained each target institution in 1983 and the group which contained that institution in 1978.

For the cluster comparisons, two values for kappa were computed for each target institution, since kappa is sensitive to the differences in group size which often occur in comparing two intact clusters. Kappa can be standardized by dividing the obtained kappa with the maximum kappa possible given the size of the groups. Standardized kappa is defined as:

$$k_{standardized} = k/[(p_{om} - p_c)/(1 - p_c)]$$

where: p_{om} = The maximum proportion of possible agreements between groups

p_c = The proportion of agreements expected by chance

Both kappa and the standardized kappa are reported for the reader's information; standardized kappa was used for comparisons between methods. The a priori alpha for all comparisons was set at .05.

Comparison Regarding the Reliability of the Two Procedures

The standardized kappa values were transformed using an arcsine transformation for the purpose of comparing the reliability of the two procedures. The transformation can be expressed by:

$$k^* = 2 \times \arcsin \sqrt{k}$$

This transformation is effective in stabilizing the variances when the basic observations are proportions (Winer, 1971), thus making parametric comparisons possible (Edelbrock, 1979).

To determine the difference between the reliability of the two procedures across time, paired t-tests were used to test the difference between the average transformed standardized kappa coefficients for focal proximity analysis and those for cluster analysis for each sample.

Comparability of Procedures

Agreement between the two methods at a single point in time was determined by using kappa to compare the peer groups formed by focal proximity analysis in 1983 with the peer groups formed by cluster analysis in 1983. Kappa was computed for agreement between the focal proximity group formed for each of the 20 target institutions and the cluster that contains that target institution. These kappa values were then averaged, resulting in one agreement value for each sample. A one-sample t-test was used to test the transformed standardized kappa coefficients for each sample against zero, or chance agreement.

Importance of Variables

Following the comparisons of peer groups, the variables used to form the groups were evaluated for their relative importance in determining group assignment. Descriptive discriminant analysis was performed. The variables were examined in regard to the contribution of each variable when taken alone and while controlling for all other variables.

The correlation structure between the discriminant functions and the predictor variables was used to determine the role of the variables when taken alone. This was accomplished by interpreting the coefficients of the first discriminant function in the total canonical structure. Interpretation of these correlations provide a direct representation of which variables are most closely aligned with the underlying trait represented by the discriminant function (Meredith, 1964; Porebski, 1966; Darlington, Weinberg, & Walberg, 1973). The interpretation of the discriminant function-variable correlation is parallel to the interpretation of factor loadings in factor analysis (Stevens, 1986).

The interpretation of the standardized canonical coefficients for the first discriminant function was used to determine the relative importance of each variable controlling for all other variables. These coefficients are analogous to beta weights in multiple regression analysis.

In this study, discriminant analysis is used only in a descriptive sense, that is, to describe the relative importance of the predictor variables in the assignment of institutions to a priori determined groups.

Normally, the use of discriminant analysis assumes mutually exclusive groups of observations. In this analysis, the groups formed by focal proximity analysis are not mutually exclusive. However, since discriminant analysis was used only in a descriptive sense, the violation of this assumption was deemed acceptable. If an institution appeared multiple times, it was simply allowed to appear and was interpreted at each appearance as a point-in-time observation of institutions of that type, or as a sample of what could occur.

CHAPTER FOUR

Results

The purpose of this study was to compare two grouping procedures, focal proximity and cluster analysis, in forming institutional peer groups in higher education. The two procedures were examined in terms of their relative reliability, determined by the stability of group membership over a five-year period of time, and in terms of their comparability at a single point in time, measured by the degree of agreement between peer groups formed in 1983 by each of the two procedures.

Results from the Grouping Procedures:

The two procedures used to assign institutions to peer groups were focal proximity analysis and cluster analysis. Focal proximity analysis formed peer groups for two randomly selected samples of twenty target institutions. Peer groups for each institution were created based on 1983 data and 1978 data.

The focal proximity procedure produced a rank ordering of the institutions most similar to each target institution based on the Euclidian distance between institutions. The institutions thus identified as being most similar to each target institution were combined with that institution to form its peer group. Each peer group contains the target institution followed by the twenty-four institutions most similar to the target, ranked in order of decreasing similarity (see Appendix A).

The cluster procedure used was a combination of two algorithms of cluster analysis. First, Ward's method, a hierarchical algorithm, was used to identify initial clusters (Milligan, 1980). This algorithm resulted in thirteen clusters of institutions being formed on the basis of 1983 data and thirteen clusters being formed on the basis of 1978 data. The centroids of these clusters were then used as "seed points", or initial estimates of cluster centers, for a K-means clustering algorithm (Milligan, 1980). The K-means algorithm also created thirteen clusters in 1983 and thirteen clusters in 1978. Clusters containing fewer than ten institutions were not used in the study, resulting in ten viable clusters in 1983 and nine viable clusters in 1978. The institutions contained in each of these viable clusters are found in Appendix B; the target institutions located in each cluster are in bold print for sample one and are underlined for sample two. Institutions are referred to by FICE code. The FICE codes are identified by name of institution in Appendix C. A list of target institutions is provided in Appendix D.

Stability of Peer Groups Across Time:

The stability across time of the peer groups formed by each procedure was determined on the basis of agreement between peer groups formed using 1983 data and those formed using 1978 data by each of the two procedures. The measure of agreement used, kappa, is the proportion of agreement between groups after removing the agreement that can be attributed to chance (Cohen, 1960).

Kappa (k) is defined as:

$$k = (p_o - p_c)/(1 - p_c)$$

where: p_o = The proportion of observed agreements between groups

p_c = The proportion of agreements expected by chance.

Since kappa is sensitive to differences in group size, such as those which occur in comparisons of two intact clusters, the raw kappa coefficients were standardized by dividing the obtained kappa by kappa maximum. Kappa maximum is the highest possible kappa coefficient obtainable when group sizes are disparate. For example, with two groups made up of 30 and 40 institutions respectively, the highest possible agreement would be 30 institutions in common. Kappa standardized can be expressed as:

$$k_{standardized} = k/[(p_{om} - p_c)/(1 - p_c)]$$

TABLE 1 RAW, STANDARDIZED AND TRANSFORMED KAPPA COEFFICIENTS, MEANS AND STANDARD DEVIATIONS: FOCAL PROXIMITY ANALYSIS--SAMPLE ONE.

INSTITUTION	RAW KAPPA	STANDARDIZED KAPPA	TRANSFORMED KAPPA
2519	.570238	.570238	1.711739
1892	.785119	.785119	2.177592
2005	.398333	.398333	1.366035
1999	.699167	.699167	1.980495
2008	.355357	.355357	1.27731
3639	.398333	.398333	1.366035
3749	.269405	.269405	1.091460
1574	.484386	.484386	1.539363
1976	.656191	.656191	1.888495
3379	.785119	.785119	2.177592
1147	.570238	.570238	1.711739
3322	.527262	.527262	1.625347
1157	.398333	.398333	1.366035
2188	.226429	.226429	.991849
1950	.484286	.484286	1.539363
1051	.570238	.570238	1.711739
2551	.613214	.613214	1.799206
3599	.312381	.312381	1.186143
2243	.570238	.570238	1.711739
3581	.398333	.398333	1.366035
$\bar{X}$	.503625	.503625	1.579266
s	.160	.160	.333

TABLE 2 RAW, STANDARDIZED AND TRANSFORMED KAPPA COEFFICIENTS, MEANS AND STANDARD DEVIATIONS: FOCAL PROXIMITY ANALYSIS--SAMPLE TWO.

INSTITUTION	RAW KAPPA	STANDARDIZED KAPPA	TRANSFORMED KAPPA
1977	.484286	.484286	1.539363
3032	.570238	.570238	1.711739
1140	.441310	.441310	1.453144
1083	.785119	.785119	2.177592
3658	.828095	.828095	2.286555
3896	.484286	.484286	1.539363
2015	.441310	.441310	1.453144
1372	.226429	.226429	.991849
3100	.441310	.441310	1.453144
3656	.656191	.656191	1.888495
2847	.527262	.527262	1.625347
3615	.656191	.656191	1.888495
6740	.441310	.441310	1.453144
1786	.570238	.570238	1.711739
1092	.441310	.441310	1.453144
2653	.226429	.226429	.991849
1156	.484286	.484286	1.539363
2554	.570238	.570238	1.711739
1602	.484286	.484286	1.539363
3448	.785119	.785119	2.177592
$\bar{X}$	.527262	.527262	1.629308
s	.160	.160	.339

TABLE 3 RAW, STANDARDIZED AND TRANSFORMED KAPPA COEFFICIENTS, MEANS AND STANDARD DEVIATIONS: CLUSTER ANALYSIS--SAMPLE ONE.

INSTITUTION		RAW KAPPA	STANDARDIZED KAPPA	TRANSFORMED KAPPA
2519		.184874	.268698	1.089866
1892		.398534	.453030	1.476718
2005		-.102885	-.108954	-.672780
1999		.475991	.694275	1.969854
2008		-.071650	-.088989	-.605844
3639		.045168	.071383	.540921
3749		-.039937	-.118080	-.701554
1574		.558700	.773668	2.149973
1976		.520524	.532686	1.636215
3379		.398534	.453030	1.476718
1147		-.071650	-.088989	-.605844
3322		.083273	.112448	.683917
1157		.009232	.011260	.212626
2188		-.102885	-.108954	-.108954
1950		.620865	.710679	2.005739
1051		.398534	.453030	1.476718
2551		.497692	.509320	1.589438
3599		.520524	.532686	1.636215
2243		.558700	.773668	2.149973
3581		.483333	.588343	1.748416
	$\bar{X}$	.268273	.321212	.929225
	s	.269	.329	1.063

TABLE 4 RAW, STANDARDIZED AND TRANSFORMED KAPPA COEFFICIENTS, MEANS AND STANDARD DEVIATIONS: CLUSTER ANALYSIS--SAMPLE TWO.

INSTITUTION	RAW KAPPA	STANDARDIZED KAPPA	TRANSFORMED KAPPA
1977	.520524	.532686	1.636215
3032	.475991	.694275	1.969854
1140	.620865	.710679	2.005739
1083	.493965	.508253	1.587303
3658	.398534	.453030	1.476718
3896	.620865	.710679	2.005739
2015	.184874	.268698	1.089866
1372	.006510	.008242	.181819
3100	.620865	.710679	2.005739
3656	.205001	.297950	1.154801
2847	.257106	.269625	1.091956
3615	.483333	.588343	1.748416
6740	.558700	.773668	2.149973
1786	.652459	.746844	2.087123
1092	.520524	.532686	1.636215
2653	.045168	.071383	.540921
1156	.620865	.710679	2.005739
2554	.293281	.297245	1.153259
1602	.558700	.773668	2.149973
3448	.475991	.694275	1.969854
$\overline{X}$	.430706	.517679	1.582361
s	.198	.239	.555

where: p_{om} = The maximum proportion of possible agreements between groups

p_c = The proportion of agreements expected by chance.

Following standardization of kappa, an arcsine transformation was performed to make parametric comparisons possible.

Table 1 through Table 4 present the raw, standardized and transformed kappa coefficients for each sample by each procedure, including means and standard deviations. When there is no difference in the size of the groups being compared, the raw kappa and the standardized kappa will be identical.

The first analysis examined the stability of the peer groups formed by each procedure independently. This was accomplished by testing the difference between the average transformed kappa (k*) for each procedure (which measured agreement between the groups formed by that procedure in 1983 and those formed in 1978) and zero (which represented chance agreement between these groups). These differences were tested using single-sample t-tests. The results of these tests are shown in Table 5.

These data indicate that the average transformed kappa (k*) was found to be greater than chance for each procedure for each sample (original sample and replication sample). Note that there was more variability of the k* coefficients for institutions under cluster analysis.

TABLE 5 TEST OF TRANSFORMED VALUES OF KAPPA FOR EACH PROCEDURE AGAINST CHANCE AGREEMENT

	k(stand.)		k*			
PROCEDURE & SAMPLE	$\bar{X}$	s	$\bar{X}$	s	No. of obs.	t
Sample One						
Focal Proximity	.5036	.160	1.5793	.333	20	21.21*
Cluster	.3212	.329	.9292	1.063	20	3.91*
Sample Two						
Focal Proximity	.5273	.160	1.6293	.339	20	21.47*
Cluster	.5177	.239	1.5824	.555	20	12.75*

*p<.0005

Comparison Regarding the Reliability of the Two Procedures:

The second analysis compared the reliability of the two procedures. This comparison was made on the basis of the difference between the average transformed kappa coefficients for focal proximity analysis and those for cluster analysis. This difference was tested using paired t-tests to test each sample. For sample one, focal proximity analysis was more reliable than cluster analysis in assigning institutions to peer groups ($t=3.15$, $p<.05$). There was no difference between the two methods for sample two ($t=.40$, $p>.05$)(See Table 6).

As indicated earlier, the reliability of a procedure is measured by stability across time of the groups formed by that method, utilizing kappa as the measure of agreement. It was anticipated that the two procedures would differ in reliability, with focal proximity expected to create more stable groups for any given institution.

This expectation was based on the fact that focal proximity takes a single, target institution and forms a peer group around that institution. The target institution is thus located at or near the centroid of its appointed group. Focal proximity analysis is not based on requirements that group memberships be mutually exclusive.

Cluster analysis, on the other hand, maps out a population of institutions into mutually exclusive groups.

TABLE 6 TEST OF RELIABILITY OF FOCAL PROXIMITY ANALYSIS VS CLUSTER ANALYSIS FOR TWO SAMPLES

	k(stand.)				k*				
SAMPLE	$\bar{X}$ (focal proximity)	s	$\bar{X}$ (cluster analysis)	s	$\bar{X}$ (focal proximity)	s	$\bar{X}$ (cluster analysis)	s	t
Sample One	.5036	.160	.3212	.329	1.5793	.333	.9292	1.063	3.15*
Sample Two	.5273	.160	.5177	.239	1.6293	.339	1.5824	.555	.40

*p<.0025

A given institution could be located on the periphery of the group to which it is assigned and could conceivably be more similar to institutions at the periphery of neighboring groups than to other institutions at the opposite periphery of its own group.

Implications for Individual Institutions:

The location of an institution within the space of its peer group would appear to have clear implications for group stability relative to that institution. For a centrally located institution, routine data fluctuations over time might be expected to cause some of its peer institutions to change group membership, particularly those located at greatest distance from the target institution. On the other hand, an institution located on the periphery of its group, as can occur in groups formed by cluster analysis, would be expected to have less stability, with the possibility of data fluctuations resulting in re-assignment of the target institution to a neighboring group and hence a radical turn-over in institutional peers.

In order to evaluate the actual impact on peer group stability for peripherally located institutions, those institutions which were located in the outer third of their respective cluster peer group in 1978 were examined. Five such institutions were identified. Similarly, the five institutions located most centrally in their respective

TABLE 7 STANDARDIZED KAPPA COEFFICIENTS FOR PERIPHERALLY LOCATED INSTITUTIONS

INSTITUTION	DISTANCE FROM CENTROID IN 1978	k (focal proximity)	k (cluster analysis)	DISTANCE FROM CENTROID IN 1983
1157	.98	.398333	.011260	.53
1156	.81	.484286	.710679	.57
2243	.79	.570238	.773668	.90
2653	.78	.226429	.071383	.96
1950	.77	.484286	.710679	.56

TABLE 8 STANDARDIZED KAPPA COEFFICIENTS FOR CENTRALLY LOCATED INSTITUTIONS

INSTITUTION	DISTANCE FROM CENTROID IN 1978	k (focal proximity)	k (cluster analysis)	DISTANCE FROM CENTROID IN 1983
2847	.21	.527262	.269625	.74
1083	.25	.785119	.508253	.10
1602	.31	.484286	.773668	.47
3448	.37	.785119	.694275	.67
1051	.37	.570238	.453030	.15

cluster peer groups in 1978 were examined. Tables 7 and 8 present the standardized raw kappa coefficients for these institutions under focal proximity analysis and cluster analysis. These kappa coefficients are measures of the agreement between the 1983 and 1978 peer group formed for each institution. They represent the stability of the peer groups formed by each procedure and hence reflect the reliability of the procedures used to form the groups. No clear pattern emerged from these data linking location of target institution to peer group stability.

Comparability of Procedures:

The third analysis was a comparison of the groups formed by each of the procedures at a single point in time--1983. This comparison was based on the agreement between the groups formed for each of the target institutions in 1983 by focal proximity and the groups formed in 1983 by cluster analysis which contained each target institution. Tables 9 and 10 present the raw, standardized and transformed kappa coefficients for agreement between procedures for each sample, including means and standard deviations.

A one-sample t-test was used to test the transformed kappa coefficients, which represented agreement between groups formed by the two procedures, against zero, or chance agreement. As shown in Table 11, agreement between groups

TABLE 9 RAW, STANDARDIZED AND TRANSFORMED KAPPA COEFFICIENTS, MEANS AND STANDARD DEVIATIONS: AGREEMENT BETWEEN FOCAL PROXIMITY AND CLUSTER ANALYSES--SAMPLE ONE IN 1983

INSTITUTION	RAW KAPPA	STANDARDIZED KAPPA	TRANSFORMED KAPPA
2519	.603993	.603993	1.780312
1892	.449695	.449695	1.470016
2005	.356506	.356506	1.279715
1999	.415290	.415290	1.400555
2008	.313607	.313607	1.188786
3639	.269405	.269405	1.091460
3749	.415290	.415290	1.400555
1574	.484286	.484286	1.539363
1976	.550660	.550660	1.672290
3379	.587271	.587271	1.746238
1147	.335056	.335056	1.234612
3322	.453814	.453814	1.478293
1157	.577593	.577593	1.726611
2188	.399406	.399406	1.368225
1950	.137602	.137602	.760057
1051	.174543	.174543	.862008
2551	.505726	.505726	1.582248
3599	.528193	.528193	1.627212
2243	.398333	.398333	1.366035
3581	.313607	.313607	1.188786
$\bar{X}$	.413494	.413494	1.388169
s	.131	.131	.280

TABLE 10 RAW, STANDARDIZED AND TRANSFORMED KAPPA COEFFICIENTS, MEANS AND STANDARD DEVIATIONS: AGREEMENT BETWEEN FOCAL PROXIMITY AND CLUSTER ANALYSES--SAMPLE TWO IN 1983

INSTITUTION	RAW KAPPA	STANDARDIZED KAPPA	TRANSFORMED KAPPA
1977	.573127	.573127	1.717576
3032	.883058	.883058	2.443572
1140	.310081	.310081	1.181176
1083	.477210	.477210	1.525201
3658	.697332	.697332	1.976499
3896	.367575	.367575	1.302747
2015	.392789	.392789	1.354697
1372	.348457	.348457	1.262866
3100	.310081	.310081	1.181176
3656	.207986	.207986	.947114
2847	.467552	.467552	1.505854
3615	.399406	.399406	1.368225
6740	.312381	.312381	1.186143
1786	.281335	.281335	1.181679
1092	.640528	.640528	1.855690
2653	.656192	.656192	1.888495
1156	.166348	.166348	.840214
2554	.419190	.419190	1.408464
1602	.312381	.312381	1.186143
3448	.184141	.184141	.879952
$\bar{X}$	.420221	.420221	1.409674
s	.187	.187	.401

TABLE 11 TEST OF TRANSFORMED VALUES OF KAPPA AGAINST CHANCE AGREEMENT BETWEEN FOCAL PROXIMITY AND CLUSTER ANALYSIS IN 1983

	k(stand.)		k*			
PROCEDURE & SAMPLE	$\bar{X}$	s	$\bar{X}$	s	No. of obs.	t
Sample One	.4135	.131	1.3882	.280	20	22.20*
Sample Two	.4202	.187	1.4097	.401	20	15.74*

*p<.0005

formed by focal proximity analysis in 1983 and those formed by cluster at the same point in time was greater than could be expected by chance (Sample 1: $t=22.2$, $p<.05$; Sample 2: $t=15.74$, $p<.05$).

Importance of Variables:

The final stage of data analysis was an examination of the relative importance of the variables used as criteria for peer group assignment. This analysis used the focal proximity procedure using 1983 data, thus using the more reliable method and the most current data. Though not a primary focus of this study, the role of the variables used in the grouping process is not trivial. Discriminant analysis was utilized to explore the contribution of each of the variables to the assignment of institutions to groups. The variables were examined in regard to the contribution of each variable when taken alone and after controlling for all other variables.

This contribution of each variable when taken alone was examined through the interpretation of the first discriminant function coefficients in the total canonical structure. These coefficients represent the product-moment correlation between the discriminant function and the variable and can be used to identify the type of information carried by the function which was most useful in discriminating between groups. When the absolute value of

TABLE 12 TOTAL STRUCTURE COEFFICIENTS FOR THE FIRST DISCRIMINANT FUNCTION

VARIABLE	COEFFICIENT
PHD	.7650
LRES	.7035
LFTE	.6942
EDUC	-.6851
NLAW	.6736
BA	-.6069
ENG	.4860
SOCSCI	.4745
MA	.4725
HUMAN	.3874
ARTS	.3370
HEALTH	.3062
SCI	.2780
PT	.2303
BUS	-.1517
AG	-.1437

the coefficient approaches one, the function and the variable are carrying nearly identical information. If the coefficient is near zero, the function and the variable share little information (Klecka, 1987). The total structure coefficients for the first discriminant function are shown in descending order in Table 12.

The variables which were most closely associated with the first discriminant function were PHD (proportion of degrees at the doctoral level to total degrees awarded) and LRES (research expenditures). Both of these variables are measures of an institution's research emphasis. LFTE (FTE enrollment), EDUC (proportion of degrees awarded in education to total degrees awarded), NLAW (proportion of degrees awarded in law to total degrees awarded), and BA (proportion of degrees at the bachelor level to total degreed awarded) were also revealed to be more important variables.

The interpretation of the standardized canonical coefficients for the first discriminant function was used to determine the relative importance of each variable while controlling for all other variables. These coefficients are analogous to beta weights in multiple regression analysis. The variables which contributed most to group discrimination were BA and MA (proportion of degrees at the master's degree to total degrees awarded). EDUC, NLAW, and LFTE (FTE enrollment) were also shown to be more discriminating variables. The standardized coefficients for the first discriminant function are shown in descending order or relative importance in Table 13.

TABLE 13 STANDARDIZED COEFFICIENTS FOR THE FIRST DISCRIMINANT FUNCTION

VARIABLE	COEFFICIENT
BA	-1.7865
MA	-1.0280
EDUC	-.4360
NLAW	.3939
LFTE	.3741
HUMAN	.2466
HEALTH	.2421
ARTS	.1787
SOCSCI	.1468
PT	.1431
BUS	.0747
AG	-.0486
LRES	.0480
SCI	.0441
ENG	.0385
PHD	.0000

CHAPTER FIVE

Summary of Results

The use of institutional peer groups as a context for decision making and planning is an established practice in higher education. Comparative studies based on peer data can support all stages of the planning process. In the initial stages of planning, comparative studies provide reference points, or benchmarks, regarding an institution's current position. Throughout the time frame encompassed by the planning process, these studies provide a context to measure a pattern of relative standing through longitudinal studies or trend analysis.

The appropriate use of comparative analysis based on a peer group in higher education planning is greatly enhanced by an awareness of the stability of the peer group used as the basis of the analysis. If an acceptable level of stability is present, then those who use the peer group as a basis for comparative analyses can feel a degree of confidence in the meaningfulness of comparisons and in the decisions made as a result of the comparisons.

This stability is also an indication of the reliability of the procedure used to form the peer group, since the reliability of a procedure can be determined as a function of its ability to replicate peer group assignment of colleges and universities at different points in time.

Therefore, a stable peer group provides those who are responsible for creating the peer group with a positive indication of the reliability of the procedure used.

On the other hand, if a peer group is not stable, then those using it would be well advised to reconsider its appropriate useage and those who created it would be well advised to reconsider the methodology by which it was created. No doubt, there are instances in which the stability of a peer group is not of great concern, namely when the decisions to be made can appropriately be informed within a current "snapshot" context and do not have long term consequences. However, this is generally not the case in the planning processes of higher education.

Although a few studies have compared the agreement between groups formed by different procedures at a single point in time (Teeter & Christal, 1987; Makowski & Wulfberg, 1980), there have been no studies examining the agreement between groups formed by a particular method at different points in time--in other words, the stability of institutional peer groups or the reliability of the procedures used to form these groups.

This study was designed to fill this void by determining and comparing the reliability of two procedures, focal proximity and cluster analysis, in regard to assigning institutions of higher education to peer groups.

Specifically, the two procedures for forming peer groups were compared based on (1) the stability of peer group membership over time and (2) on the degree of agreement between peer groups formed by each of the two procedures at a single point in time.

Stability of peer group membership over time was examined in two separate analyses. The first analysis examined the stability of the groups formed by each procedure independently. This stability was defined as the degree of agreement in membership between groups formed by the procedure using 1983 data and groups formed by the procedure using 1978 data. Results revealed this level of agreement to be greater than chance for both cluster analysis and focal proximity analysis. There was more variability of group agreement among individual target institutions under cluster analysis.

The second analysis compared the reliability of the two procedures as a function of group stability. For one sample of institutions, focal proximity was found to be more reliable than cluster analysis in assigning institutions to peer groups. There was no difference between the two methods for a second sample of institutions. A comparison of the two methods in terms of stability of peer groups for individual institutions located on the periphery and near the center of their respective cluster peer groups revealed no clear pattern linking location of target institution to peer group stability for either method.

The third analysis was a comparison of the groups formed by each of the procedures at a single point in time--1983. For both samples of institutions, agreement between groups formed by focal proximity analysis in 1983 and those formed by cluster analysis at the same point in time was greater than could be expected by chance.

Finally, the data were examined to determine the importance of the variables used as criteria for peer group analysis. The variables that loaded most highly on the first discriminant function of the total canonical structure were PHD (proportion of degrees at the doctoral level to total degrees awarded) and LRES (research expenditures). The variables that were most important when holding all other variables constant were BA (proportion of degrees awarded at the bachelor level to total degrees awarded) and MA (proportion of degrees awarded at the master's level to total degrees awarded).

Conclusions

Stability of Groups/Reliability of Procedures

The question of the ability of focal proximity analysis and cluster analysis to form peer groups which remain relatively stable across time was answered in statistical terms relative to chance "stability", or chance agreement between groups. While the answer was affirmative in these terms across the aggregate of institutions via the use of the average kappa coefficient for each procedure, the answer to this question in practical terms and for individual institutions is not clear.

In practical terms, central questions are:

1. How much agreement between groups across time is necessary for "relative stability" to exist?

2. How much stability is required for a "good" peer group? For what purpose?

3. How long should a peer group remain stable? Again, for what purpose?

In terms of individual institutions, there is a great deal of variability in the stability of the peer groups formed by the procedures. Standardized kappa coefficients (k_s) for focal proximity analysis ranged from a high of .828 to a low of .226, while for cluster analysis the coefficients ranged from .774 to -.118, with five institutions having negative coefficients, representing less than chance agreement. These results provide no assurance that either procedure could produce a meaningfully stable peer group for any given institution.

These findings lead to another practical question: Can a statistical procedure alone be used to form stable peer groups? Though this study does not address every known grouping procedure and cannot provide a definitive answer to this question, these findings clearly agree with those who would hold that statistical grouping procedures are simply a tool in the peer selection process, meant to inform such a process rather than becoming or replacing the process itself.

However, if procedures such as those evaluated here are utilized as tools in the peer selection process, then the present findings do provide insight into the issue of which is the more reliable procedure. Focal proximity analysis was significantly more reliable than cluster analysis for the first sample of 20 institutions and produced a slightly higher mean standardized kappa coefficient (k_s) for the second sample, though not significantly higher. Focal proximity analysis also was more consistent in terms of the stability of the peer groups it formed for individual institutions.

Nearly one-fourth of the peer group formed using cluster analysis had standardized kappa (k_s) coefficients of .10 or less and another one-fourth had k_s coefficients greater than .70. All focal proximity peer groups had k_s coefficients between .226 and .828, with approximately 73% having k_s coefficients greater than .40.

The source of the inconsistency in cluster analysis is not clear. The attempt to relate peer group stability to the location of the target institution within the space of its peer group (centrally located vs. peripherally located) was inconclusive. It was anticipated that focal proximity analysis would be clearly superior in producing stable peer groups for institutions located near the periphery of their cluster analysis peer group, since in focal proximity, the peer group was formed around that specific target institution. However, this superiority was not demonstrated.

There are several possible explanations for this finding, apart from the possibility that there is no relationship between target location and group stability. For example, it is possible that the targets selected for examination did not represent sufficient extremes of distance between the centrally located (innermost third) and the 5 most peripherally located institutions.

Another possibility which might explain the absence of a clear link between location and the ability of the two procedures to produce stable groups is related to the questionable validity of the assumption that, for focal proximity, the target institutions are located at the center of the group. For example, it is possible that the 24 institutions nearest a target could all be on one dimension of the group's space. In fact, this arrangement might be expected when an institution is an extreme case of any particular type of institution, for instance, the largest, wealthiest comprehensive four-year institution in a group of 25 such institutions. Thus, even under focal proximity analysis, an institution may be located on the periphery of its group. By definition, it is still central within its group's total space, but in reality, all other institutions lie on one side of the target.

Finally, no attempt was made to measure institutional growth rate, mission changes or other measures of institutional change that might provide explanation of peer group mobility that is somewhat independent of the procedures employed. Institutions change at different rates and in different directions and little has been done to either investigate or model institutional change in higher education. Thus the effects of such change on the stability of peer groups and the reliability of the procedures used to form them are unknown.

Comparability of Procedures at a Single Point In Time

The question of comparability of procedures, or agreement between groups formed by different procedures at a single point in time, was answered in statistical terms relative to chance agreement between groups formed by cluster analysis in 1983 and those formed by focal proximity analysis in 1983. For both samples examined, the agreement between procedures was greater than could be expected by chance.

For sample two, the k_s coefficient for agreement between procedures at a single point in time was lower than the k_s coefficients for agreement across time for each of the two procedures, revealing less agreement between cluster analysis and focal proximity analysis at a single point in time than between groups formed by cluster analysis five years apart and groups formed by focal proximity analysis five years apart. These data are not encouraging regarding the use of these statistical procedures alone to form meaningful peer groups. However, as was noted above, it is the contention here that such procedures be used in conjunction with other data based and judgmental procedures to form peer groups, rather than using such procedures in isolation.

Importance of Variable

Interpretation of the first total structure discriminant function reveals that the dimension that contributed the greatest discrimination between groups was research emphasis. The two variables with the highest positive loadings on the first function were PHD (proportion of doctoral degrees to total degrees awarded) and LRES (research expenditures), both measures of research emphasis. More specifically, the first discriminant function would appear to define major research universities. The high positive loading on LFTE (FTE enrollment) and NLAW (proportion of law degrees) and high negative loadings on EDUC (proportion of degrees awarded in education) and BA (proportion of bachelors degrees to total degrees awarded) are consistent with this interpretation.

Interpretation of the standardized canonical coefficients indicate the proportion of degrees at the bachelor level and proportion of degrees at the master's level to be by far the most important variables in determining the discriminant scores which serve as the basis for assigning institutions to peer groups. These variables are negatively related to the discriminant score.

Note that these variables represent the complement of PHD, the variable with the highest loading in the total canonical structure coefficients. Also note that the standardized coefficient for PHD is .0000, due to the overlap in variance resulting from the use of all three degree levels as criteria in this analysis. This has led to a near singularity of the within groups variance/covariance matrix and is a function of the lack of independence of these three variables. Since these three proportions sum to nearly one (the sum is not quite one, since professional degrees are not included), researchers must consider not using all three degree levels in future research.

Recommendations

This research has clear applications and implications both for those who are responsible for selecting institutional peer groups and for those who use institutional peer groups as a basis for conducting comparative analyses in higher education. First, for those who select institutional peer groups, this study provides a methodology for measuring the stability of peer groups and determining the reliability of procedures used to create them.

Also, for those who select peer groups, the findings of this study should cast strong doubt on the efficacy of using a statistical procedure alone as the only basis for institutional peer group assignment. Statistical procedures are clearly a key element in the institutional peer grouping process due to the objectivity that they lend to the process and the credibility that results from this objectivity. However, it is more likely that viable, stable institutional peer groups would result from the combination of a statistical procedure and informed judgment. This assumed enhancement of the peer grouping process as a result of combining statistics and judgment is an area in need of further study.

Another area for further research concerns the practical questions raised earlier in this chapter. These questions were:

1. How much agreement between groups across time is necessary for "relative stability" to exist?

2. How much stability is required for a "good" peer group? For what purpose?

3. How long should a peer group remain stable? Again, for what purpose?

If one were to accept that 80% of an original peer group should remain peers over a five year period of time for practical stability to exist for the purpose of long range planning, both procedures examined would fail the test for the aggregate of institutions. Eighty percent agreement for focal proximity peer groups in this study would represent a standardized kappa coefficient (k_s) of .785. The highest mean k_s obtained was .527 for sample two under focal proximity analysis.

Even for researchers who might argue the importance of the role that stability plays in peer grouping, an important point to consider is that reliability measures provide the basis for the upper boundary of validity. It is not necessary to measure reliability at five year intervals--perhaps one year or even six months would be more appropriate--but, in any case, if reliability cannot be established in the peer grouping process, then neither can validity. This determination of shorter-term reliability is another area in need of additional research.

Four other areas were identified by this study as needing additional research. First, there should be more in-depth examination of the relationship between group stability and the location of a target institution within its peer group space. Perhaps a larger sample of institutions located deeper in the extreme periphery and center of their respective groups would provide more definitive information about this relationship, if it exists.

Another area for further research concerns the relationship of stability to peer group size and homogeneity. Do larger groups tend to be more stable? Do more stable groups tend to be more homogeneous? Also, there is a need for research regarding models of change in higher education. Can a measure of change be incorporated as a criterion for peer group selection? Finally, the variables used to form peer groups should be evaluated to determine the role they play in the stability of peer groups.

The implications for those who use institutional peer groups as a basis for comparative analyses are similar to those already stated. The primary point for these users is the need to be informed users. They should determine if stability is an issue for their particular use(s) of comparative data and expect information from the creators of their particular peer group regarding the manner in which it was formed and the degree to which it is stable. The user should also bear in mind that if reliability cannot be established for the process that created a peer group, validity is questionable.

As stated in Chapter One of this document, there are no absolute norms in higher education to be used as guidelines for decision making. Nor, given the diverse and changing nature of higher education, can there be. In the face of any weaknesses in the processes of selecting institutional peers, comparative analysis is still one of the best resources available to decision makers in higher education. The intent of this study is not to undermine confidence in the efficacy of comparative analysis, but rather to provide information that may lead to strengthening the foundation upon which the process is based.

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Appendix A

Peer Groups Formed Focal Proximity Analysis

1983 Groups--Sample One

2519	**1892**	**2005**	**1999**	**2008**	**3639**	**3749**	**1574**	**1976**	**3379**
2569	3371	2501	10313	2031	3565	1101	1759	3456	2329
1138	1809	3315	3448	2053	3630	1141	3152	2651	10313
2015	1948	2503	2329	3581	1694	9762	11711	3815	29013
2083	3125	3316	29013	3510	1601	2307	1812	1601	9092
10115	3223	2551	3032	2905	3625	3474	9168	2002	2837
2479	1610	1090	3184	3661	1573	3642	2259	1927	1999
2554	1737	3541	3509	3145	3815	3448	3815	1812	1776
2360	3675	2024	2837	1090	2651	3216	2651	2906	3827
1481	3798	3510	2259	1780	1976	1138	3509	1915	3675
3926	3896	2360	3652	3954	3152	1157	1140	2495	1948
3955	29013	2377	1610	3523	2905	3032	1816	1926	3448
1693	1786	1963	3123	2906	3154	29013	1999	3624	3896
1141	3448	1780	1948	3932	2017	1537	1047	2454	1083
3529	3051	3529	9168	3529	1926	1051	1694	2259	3895
1537	1154	3771	1759	2410	3456	2841	1815	1090	6968
3326	1083	3775	3896	2657	2495	2330	3896	2496	1312
3510	1489	3919	2015	1963	11161	2950	2015	9563	3530
3592	9092	2495	3642	2005	1572	1999	6740	1572	9168
29100	2329	1977	1140	2501	1977	1156	3652	1977	1610
9741	1155	2006	3675	9235	2981	9630	2243	1694	3798
2099	10313	3325	2330	3487	1090	2099	2330	2410	1989
3954	2010	8810	3131	1144	1927	3675	10313	1573	3184
9635	3735	1890	3530	2015	2496	1142	11161	3599	3652
2330	1081	3926	3474	2568	2259	2554	2329	3630	2221

1147	**3322**	**1157**	**2188**	**1950**	**1051**	**2551**	**3599**	**2243**	**3581**
1146	2844	7993	2394	9168	3448	3599	2551	1047	3661
2589	2846	1142	2975	2307	1989	3316	2622	1759	3145
2031	1004	1141	9630	2568	2010	2403	1572	1574	3529
3800	3802	1156	3592	1140	3005	2005	3815	1602	3728
1989	3925	1138	2301	2021	3675	2024	3328	1002	3487
1431	2617	2841	2099	3728	1489	1016	9563	2651	2568
1780	3321	3326	3219	1057	3184	1572	3316	3152	1082
2099	2625	2307	3478	3661	1150	2501	2403	3509	1963
3510	1616	9333	3315	2613	1948	1098	1890	3926	3954
1150	2210	3216	3917	3487	3018	3771	2906	10115	9563
2516	2609	2099	3721	3896	2440	3315	3456	2330	1693
2503	2642	1693	2377	9630	29013	3325	2024	1815	2015
3775	3324	2083	9635	3581	3775	2495	2495	3815	2360
1009	2923	2519	2360	1155	3510	3919	1020	2015	2008
1090	3223	2388	8810	3656	3530	2503	1693	3652	2906
9630	2842	8310	2841	2020	2031	2566	3152	6740	1020
1963	2976	9741	3325	2330	2307	3529	3529	1349	2622
1758	2336	9630	8310	1827	2330	1890	3764	2569	3328
3721	1137	3749	1425	3529	3644	1020	3919	1601	2441
3932	1156	9930	3775	1737	2441	2360	3154	9168	1890
2005	2189	4509	2005	2259	3721	2017	3487	2454	1090
2657	1692	2554	3316	29100	2008	1674	1927	3624	2975
3606	1890	2569	1616	2441	1537	3328	1090	2259	3325
1692	3606	29100	1016	2099	1758	9563	2005	2519	2024

Peer Groups Formed in 1983 by Focal Proximity Analysis

Sample Two

1977	**3032**	**1140**	**1083**	**3658**	**3896**	**2015**	**1372**	**3100**	**3656**
1090	3131	2259	3530	2010	1140	2330	1016	3018	1155
3665	3652	3896	2221	1535	1610	1693	2403	2690	3728
2495	1999	9168	29013	6883	9168	1138	3771	3223	1150
2024	3642	2330	1598	2103	1737	1537	1585	2842	1537
1915	3123	3051	1989	1081	2330	2554	3541	1786	2330
3487	3509	1737	2010	2290	3125	2569	2006	1737	1138
2002	3474	2622	1610	3969	3051	3728	3219	1154	3145
2017	3448	1786	1775	3895	10313	3529	2566	1137	3661
3630	3184	2441	2516	3798	1155	1812	3316	1948	3896
9563	3749	2976	1535	1775	1786	3581	2551	1153	1139
2496	2329	3728	1948	6965	2329	3955	3315	1151	1081
1780	1101	10313	1081	1083	2259	3815	10115	1051	2015
2454	9636	1610	3827	1948	29013	10115	3764	3448	1151
1963	10313	2687	3184	1151	3656	2519	1674	2848	3954
1926	2837	2554	3675	3530	3728	1759	3926	1150	1610
3529	9762	1950	2103	1809	3675	3216	2501	3675	2099
2005	2518	2923	2290	3184	1759	2259	1573	1610	2031
2441	2440	2617	3448	1370	1950	3145	1098	2010	1137
3316	2950	1759	3125	2221	1154	3510	2005	3051	2975
1572	29013	1537	10313	3675	1776	3152	2083	1155	3581
3510	2015	2307	3051	9092	3448	9563	2479	2976	1950
1082	3530	2015	1758	1892	1999	1481	3592	1809	3530
2906	1759	9563	2565	3448	3827	1150	1572	1082	3414
1020	3728	3487	6965	3644	1151	2441	1020	2846	3125

2847	**3615**	**6740**	**1786**	**1092**	**2653**	**1156**	**2554**	**1602**	**3448**
2185	2503	1759	3051	2024	1049	1157	3216	1047	29013
2845	8810	11711	1737	2495	1601	2841	1693	2651	1999
2105	2501	1999	2330	3154	1552	1141	2015	1927	1948
2835	3919	4509	3018	1098	1602	1142	2622	3423	3675
2836	1674	3955	1610	3665	1048	3721	1812	2314	1051
1321	2360	2015	2976	1572	1047	2301	1537	1552	1610
2849	1692	9741	2259	2017	1406	2846	2330	1815	1737
29040	1963	3216	2441	3919	1815	1138	2259	3152	2330
3696	2377	2554	1349	3316	1816	9630	1140	8310	2329
1320	3771	1812	1140	3328	1171	2836	3955	2403	1989
2850	2551	1141	9563	2981	2651	2617	29100	1573	3184
3765	1780	1574	2923	1977	1345	3216	1141	1585	10313
2843	2005	3522	1082	3315	1927	2099	3599	1016	2010
7108	2024	1815	3896	3487	1561	2845	2569	11161	1083
1156	2906	9168	2454	1926	13231	1137	4509	3815	3530
2841	3926	3423	3487	1090	3423	2687	1138	1020	1786
2848	9563	1047	9168	2551	3625	1616	2519	1759	3827
2336	1572	2651	3624	1963	11161	1154	3815	1926	1489
2690	1890	29100	1489	9563	6740	3765	2687	1561	1151
3802	3315	1693	3448	2906	2243	2307	1142	1694	3896
3721	3624	3896	29013	3764	1002	2388	1927	3474	3131
1431	2495	2259	2906	1620	2072	3219	2617	3955	3371
1146	3018	3728	1692	1020	1976	7993	9563	3926	3051
2846	3510	10313	3827	3327	1694	2844	3765	2024	2837

Peer Groups Formed in 1978 by Focal Proximity Analysis

Sample One

2519	**1892**	**2005**	**1999**	**2008**	**3639**	**3749**	**1574**	**1976**	**3379**
2569	1948	2501	3509	2053	2905	3529	1759	3456	2329
3926	3371	1090	2329	1082	9636	1141	3815	3565	10313
3955	3675	2496	2518	2377	3522	9630	1812	3815	9092
2083	2329	2551	10313	1674	1002	9635	2259	1016	3675
1616	3448	3764	3827	3624	2423	1138	2243	1927	3448
2015	1809	2017	3371	3932	1977	2975	3509	2259	3896
2554	1610	9636	3131	1780	3523	1950	2554	2002	1083
3152	3223	3315	3448	3510	1090	7022	1737	1977	3827
2360	3100	2024	3474	3018	2005	3487	9168	9563	6968
10115	9092	2905	3652	3677	1976	3954	3565	1573	2974
1481	10313	3510	3184	3696	1572	1140	2330	2642	1989
3315	3125	3541	3675	2005	1926	2360	1694	2403	3895
2479	1489	2981	3123	2503	2568	1150	2002	3599	1948
3529	2974	2566	3032	3661	9563	2569	2307	2906	29013
3145	3798	2495	1737	3665	2496	1537	1999	2981	3798
1047	2837	2503	2330	1009	3677	3955	2329	1572	3530
3592	3896	1098	9168	2501	2008	3775	3152	1694	1610
3326	3184	1674	2259	3522	3764	1142	1349	2651	3371
3935	1083	1572	2010	1431	3510	2625	3448	2905	6964
1602	3051	3599	1759	2589	2495	3216	1786	3630	2837
3510	3735	3219	3896	7104	3642	29100	1601	1812	1051
2388	1737	2006	1786	3802	3456	2188	8310	2653	2330
2625	1154	2388	2837	1090	1016	3896	3216	1005	1999
2503	3827	3955	3125	3581	3565	2554	9841	1601	3184

1147	**3322**	**1157**	**2188**	**1950**	**1051**	**2551**	**3599**	**2243**	**3581**
1146	3321	1142	3328	1140	3184	1098	2551	1759	3661
1431	1890	1156	3599	3896	3448	3599	3316	1574	3145
3665	2844	3749	1963	3749	3675	3316	2188	8310	2503
1780	2850	7022	2551	9168	3018	2566	2981	1047	2377
3696	2377	1138	1057	2020	2440	2501	3764	3815	2008
3414	1004	1141	2360	9630	2330	1090	3328	2651	1431
2589	1915	2099	3487	1759	3051	3764	2642	1602	3529
3510	3732	3954	2301	2975	1989	2336	2906	1349	1082
3800	2609	2841	2625	9635	29013	3328	2388	3326	2015
3606	3925	3219	2642	3487	1948	2495	1572	3926	2625
2568	2842	1150	3529	2617	3223	2188	1090	2410	1481
9630	3771	2617	2975	2330	3827	2981	1016	3152	1692
1610	2923	2690	2441	2441	1083	2005	1098	2083	1890
1537	3592	3592	3316	1057	1489	1674	2495	2330	3541
3487	2625	2845	3775	2307	1537	2017	9563	10115	2210
2503	2189	3529	2024	3529	2441	2388	3771	2554	3954
3775	2976	3775	2981	3123	3530	3219	2336	2002	2975
3661	2848	2367	2495	3414	1674	2906	2441	1016	1057
3932	2846	2625	3219	3661	1081	1572	2625	3448	3771
2841	3541	9635	9563	1138	1598	3919	1976	1737	3123
1989	2617	3216	3771	2015	1610	3315	1481	3456	3487
1090	1372	9630	1098	2625	1370	3771	1057	1601	1537
3471	2950	1137	2394	1537	2010	2024	1963	3509	3656
1150	2841	9930	3919	3051	6968	3510	2360	2519	3955

Peer Groups Formed in 1978 by Focal Proximity Analysis

Sample Two

1977	**3032**	**1140**	**1083**	**3658**	**3896**	**2015**	**1372**	**3100**	**3656**
1090	3131	3896	3530	3798	1140	3661	9235	3051	1776
2905	3652	1950	3827	1535	2330	1138	2844	3018	3661
9563	3123	1139	1989	3969	1610	2360	3541	1786	3145
2495	1999	2330	29013	3895	1950	1537	3771	3223	1537
2002	2440	2617	1598	2103	3051	3145	3478	1948	3954
2017	3509	1150	1758	1370	3675	3955	2388	3802	1150
1963	1101	1537	2103	6883	1537	10115	2377	1610	1431
1976	3184	1138	2010	1948	1151	1481	7104	2617	3675
1016	9762	3749	2516	2290	1139	2330	2503	2976	2015
3815	1051	1151	10313	1775	10313	2625	3592	1082	3414
2981	29013	3051	1948	6965	1150	2377	2950	1758	1155
2307	2010	2975	1610	1809	2329	2317	2006	1737	1081
2906	2837	1610	2221	1312	1737	2503	3917	2008	3896
3456	3675	2687	2565	3675	2617	9168	3219	3594	2975
2441	3448	2625	3675	2221	3448	3529	2336	2377	1610
2024	2329	9630	1535	3530	2307	2388	3775	1780	2589
9168	2518	2360	1051	1083	1081	1081	3606	1051	2210
1926	6968	3216	3448	2974	3827	1780	1890	2923	1139
3510	3145	2307	3184	3184	1083	3926	2848	1890	7108
1572	3827	1963	2329	2010	2441	2569	2849	3184	3581
3639	3005	2441	3895	1315	2975	3510	2367	1489	1370
3328	2975	2015	1081	2837	2015	3509	3315	1692	2330
3599	3371	1081	3798	1081	3216	2975	8810	1370	29013
3522	1108	3661	2330	1151	1948	2519	3765	1154	1151

2847	**3615**	**6740**	**1786**	**1092**	**2653**	**1156**	**2554**	**1602**	**3448**
2848	8810	4509	1737	1963	2403	1157	3216	3423	1051
2841	3919	3216	2976	9563	1927	2690	1693	1815	2329
2845	2501	2307	2923	2024	3456	1154	2307	8310	3371
3802	1674	2554	3051	1057	1573	1137	1481	2651	3675
2850	2377	1693	2259	2301	1345	2846	10115	1016	1948
2849	2503	1812	2454	3487	1016	1138	4509	1573	1083
3325	2024	1759	3100	2981	3925	2617	3815	2083	3184
2336	3328	1694	2330	3328	1976	2841	3326	1047	3827
2687	1780	1142	1349	2441	1572	1142	2360	2664	3896
2690	2551	1999	9563	2495	2664	2687	3152	3326	2330
1425	1963	11711	1927	1480	2651	7022	3955	3456	3051
2844	3771	1602	3594	2017	1585	1150	1694	3152	10313
2843	3606	1047	3827	9630	3478	2845	2015	1927	3223
3919	1090	10115	3509	1977	1005	1146	2519	3815	1989
2185	1692	1481	10313	2422	2950	1320	9168	2569	1737
3321	1890	3423	1092	2906	1926	2836	2330	10115	29013
3775	1082	3326	1082	1016	1602	3802	2569	2314	1999
2842	2906	1927	2441	2188	1601	1155	1812	2403	1610
1082	3510	8310	1963	2394	1098	2613	1142	4509	3509
7022	2495	2975	3018	2360	2495	3100	29100	2479	3530
1146	3775	9168	2617	2905	2906	1151	1138	9841	2974
1320	2336	2314	1759	3665	2314	1321	1927	1812	1598
2846	2388	3815	3624	2976	1599	3051	1602	2554	6968
3771	2301	3642	2002	2642	3321	2844	2975	2410	2837

Appendix B

Peer Groups Formed by Cluster Analysis

1983 Groups

#1		#2		#3	#4	#5	#6	#7	#8	#9	#10
1057	3661	1016	3630	**1051**	1004	1055	1009	1002	1005	1101	1063
1146	3721	1020	3631	1083	1081	1138	1108	1047	1345	**1999**	1149
1147	3765	1082	3665	1312	1137	1141	1143	1048	1378	2329	1314
1431	3771	1090	3764	1315	1139	1142	1144	1049	1380	2440	1316
1480	3775	1092	3815	1370	1140	1150	1313	**1574**	1406	2518	1317
1616	3802	1098	3915	1489	1151	**1157**	1350	1601	1425	2950	1320
1674	3917	1349	3926	1535	1153	1481	1626	1602	1546	3032	1321
1692	3919	1372	3935	1598	1154	1537	1758	1694	1552	3123	2105
1780	7104	1572	9563	1610	1155	1693	1825	1759	1561	3131	2185
1890	8810	1573		1775	1156	1827	1869	1812	1599	3448	2536
1963	9235	1585		1776	1737	2015	1928	1815	2072	3474	2589
2005	9630	1620		1809	1786	2083	2053	1816	2091	3509	2693
2006		1915		**1892**	**1950**	2161	2423	**2243**	2183	3642	2835
2008		1926		1948	2259	2307	2532	2651	2367	3652	2836
2020		1927		1989	2613	2314	2565	2653	2664	**3749**	2838
2031		**1976**		2010	2617	2326	2657	3152	3179	9636	2847
2099		1977		2103	2622	2330	2905	3423	3317	9762	2850
2188		2002		2221	2625	2479	2972	3565	3320	10313	3696
2189		2017		2290	2642	**2519**	3170	3625	3324		3705
2210		2021		2516	2687	2554	3210	**3639**	3407		3924
2301		2024		2688	2689	2568	3425	6740	3732		7108
2336		2403		2837	2690	2569	3471	9145			29040
2360		2410		2974	2842	2975	3523	11161			
2377		2441		3184	2844	3216	3644	11711			
2388		2454		3223	2846	3326	3677	13231			
2394		2495		3371	2923	3529	3754				
2422		2496		**3379**	2976	3592	3800				
2501		**2551**		3414	3051	3656	3921				
2503		2566		3530	3100	3728	3923				
2609		2843		3658	3125	3954	3932				
2841		2906		3675	3321	3955	3944				
2845		2981		3798	**3322**	4509	6965				
2848		3154		3827	3522	6814	9265				
2849		3219		3895	3594	7993	10366				
3005		3316		3969	3735	8310	11693				
3018		3327		4063	3896	9333					
3145		3328		6883	3925	9635					
3315		3456		6964	7022	9741					
3325		3478		6968	9168	9841					
3510		3487		9092		9930					
3541		**3599**		29013		10115					
3581		3606				11462					
3615		3624				29100					

Peer Groups Formed in 1978 by Cluster Analysis

#1		#2		#3	#4	#5	#6	#7	#8	#9
1002	3925	1004	3487	1047	1137	1009	**1051**	1425	1143	1020
1005	9168	1055	3510	1048	1138	1063	1101	2105	1144	1345
1016	9563	1057	3529	1049	1139	1083	1315	2185	1313	1378
1090	9636	1081	3541	1141	1140	1108	1489	2189	1350	1380
1092	9762	1082	**3581**	1142	1150	**1147**	1809	2336	1825	1406
1098	10115	1146	3592	1573	1151	1312	**1892**	2693	1869	1546
1349		1372	3606	**1574**	1153	1370	1948	2841	1928	1552
1572		1480	3615	1601	1154	1431	**1999**	2842	2423	1561
1926		1481	3656	1602	1155	1535	2329	2843	2532	1585
1927		1537	3661	1693	1156	1598	2440	2845	2657	1599
1963		1616	3665	1694	**1157**	1626	2518	2846	2972	2021
1976		1620	**3749**	1759	1610	1758	2631	2847	3170	2031
1977		1674	3765	1812	1737	1775	2837	2848	3210	2072
2002		1692	3771	1815	1786	1776	2974	2849	3425	2091
2005		1780	3315	1816	**1950**	1989	3032	2850	3471	2099
2017		1890	3478	1827	2454	**2008**	3123	3321	3677	2161
2188		1915	3775	**2243**	2613	2010	3125	**3322**	3754	2182
2403		2006	3917	2259	2617	2053	3131	3324	3921	2183
2410		2015	3919	2307	2687	2103	3184	3325	3923	2609
2441		2020	3926	2314	2689	2221	3223	3327	3944	2622
2495		2024	3954	2479	2690	2290	3371	3802	9265	3154
2496		2083	3955	2554	2835	2516	**3379**	3924	10366	3179
2551		2210	6814	2569	2836	2536	3448	7022	11693	3317
2566		2301	7104	2664	2923	2565	3474	29040		3320
2642		2326	7108	3152	2976	2589	3509			3407
2651		2330	8810	3423	3051	2688	3652			3721
2653		2360	9235	3625	3100	3414	3658			3728
2905		2367	9630	3630	3216	3530	3675			3732
2906		2377	9635	3815	3594	3644	3705			7993
2981		2388	29100	3935	3735	3696	3798			
3316		2394		4509	3896	3800	6968			
3326		2422		6740		3827	9092			
3328		2501		8310		3895	10313			
3456		2503		9145		3932				
3522		**2519**		9333		3969				
3523		2568		9741		6883				
3565		2625		9841		6964				
3599		2844		9930		6965				
3624		2950		11161		29013				
3631		2975		11462						
3639		3005		11711						
3642		3018		13231						
3764		3145								
3915		3219								

Appendix C

FICE Codes Identified by Institution

FICE CODE	INSTITUTION
001002	Alabama A & M
001004	Montevallo
001005	Alabama State
001009	Auburn
001016	Florence State
001020	Jacksonville State U
001047	Troy State
001048	Troy St U Doth-Ft Rk
001049	Troy St U Montgomery
001051	Alabama
001052	U Alabama Birmingham
001055	U Alabama-Huntsville
001057	U South Alabama
001063	U Alaska Fairbanks
001081	Arizona State
001082	Northern Arizona U
001083	Arizona
001090	Arkansas State
001092	U Central Arkansas
001098	Henderson State U
001101	U Arkansas Little Rock
001108	Arkansas
001137	Cal State Fullerton
001138	Cal State Hayward
001139	Cal State Long Beach
001140	Cal State LA
001141	Cal State Dominguez
001142	Cal State Santa Barbara
001143	Cal State Poly Inst
001144	Cal State Poly Pomona
001146	Cal State Chico
001147	Cal State Fresno
001149	Humboldt State U
001150	Cal State Sacramento
001151	San Diego State
001153	U S International
001154	San Francisco State
001155	San Jose State
001156	Sonoma State U
001157	Cal State Stanislaus
001312	U C Berkeley
001313	U C Davis
001314	U C Irvine

001315	U C L A
001316	U C Riverside
001317	U C San Diego
001320	U C Santa Barbara
001321	U C Santa Cruz
001345	Adams State C
001349	Northern Colorado
001350	Colorado State
001370	Colorado
001372	Western St C of Colorado
001378	Central Conn State U
001380	Western Conn State U
001406	Southern Conn St U
001425	E Conn State
001431	Delaware
001480	Florida A & M
001481	Florida Atlantic
001489	Florida State
001535	Florida
001537	U of South Florida
001546	Armstrong State C
001552	Augusta C
001561	Columbus C
001569	Georgia Tech
001572	Georgia Southern
001573	Georgia Southwestern C
001574	Georgia State
001585	North Georgia C
001598	Georgia
001599	Valdosta State C
001601	West Georgia C
001602	Georgia C
001610	Hawaii
001626	Idaho
001674	Eastern Illinois
001692	Illinois State
001693	Northeastern Illinois U
001694	Chicago State U
001737	Northern Illinois
001758	Southern Illinois
001759	Southern Illinois U Edwdv
001775	Illinois
001776	U Illinois Chicago
001780	Western Illinois
001786	Ball State
001809	Indiana
001811	Indiana U East
001812	Indiana U-Purdue U Ft W
001813	Indiana U-Purdue U Ind
001815	Indiana U Northwest

001816	Indiana U South Bend
001825	Purdue
001827	Purdue U Calumet
001869	Iowa State
001890	Northern Iowa
001892	Iowa
001915	Fort Hays State U
001926	Pittsburg State U
001927	Kansas St Teachers
001928	Kansas State
001948	Kansas
001950	Wichita State
001963	Eastern Kentucky
001976	Morehead State
001977	Murray State
001989	Kentucky
001999	Louisville
002002	Western Kentucky
002005	Nicholls State U
002006	Grambling State U
002008	Louisiana Tech U
002010	Louisiana State
002015	U of New Orleans
002017	McNeese State U
002020	Northeast La U
002021	Northwestern State U
002024	Southeastern La U
002031	U of Southwestern La
002053	Maine
002072	Frostburg State
002083	Morgan State
002091	Salisbury State C
002099	Towson State U
002102	Baltimore
002103	Maryland
002105	U Maryland Balt Co
002161	Lowell Tech Inst
002183	Bridgewater State C
002185	Framingham State C
002188	Salem State C
002189	Westfield State
002210	Southeastern Mass U
002221	Massachusetts
002243	Central Michigan
002259	Eastern Michigan
002290	Michigan State
002292	Michigan Technological U
002301	Northern Michigan
002307	Oakland U
002314	Saginaw Valley St C

002326	U Michigan Dearborn
002329	Wayne State
002330	Western Michigan
002336	Bemidji State U
002360	Mankato State U
002367	Moorhead State U
002377	St. Cloud State
002388	U Minnesota Duluth
002394	Winona State U
002403	Delta State U
002410	Jackson State
002422	Mississippi U Women
002423	Mississippi State
002440	Mississippi
002441	Southern Mississippi
002454	Central Missouri State
002479	Lincoln U
002495	NE Missouri State U
002496	NW Missouri State U
002501	SE Missouri State U
002503	SW Missouri State U
002516	Missouri
002518	U Missouri Kansas City
002519	U Missouri St Louis
002532	Montana State
002536	Montana
002551	Kearney State C
002554	U Nebraska Omaha
002565	Nebraska
002566	Wayne State C
002568	Nevada
002569	U Nevada Las Vegas
002589	New Hampshire
002609	Glassboro State C
002613	Jersey City State C
002617	Montclair State C
002622	Kean C of New Jersey
002625	Wm Patterson C of NJ
002631	Rutgers Newark C
002642	Trenton State
002651	Eastern New Mexico U
002653	New Mexico Highlands U
002654	New Mexico Inst Mng/Tech
002657	New Mexico State
002664	Western New Mexico U
002687	CUNY Brooklyn C
002688	CUNY-City College
002689	CUNY-Hunter College
002690	CUNY-Queens College
002693	CUNY-John Jay College

002835	SUNY-Albany
002836	SUNY-Binghamton
002837	SUNY-Buffalo
002838	SUNY-Stony Brook
002841	SUNY C Brockport
002842	SUNY C Buffalo
002843	SUNY-Cortland
002844	SUNY-Fredonia
002845	SUNY-Genesee
002846	SUNY C New Paltz
002847	SUNY C Oneonta
002848	SUNY-Oswego
002849	SUNY-Plattsburgh
002850	SUNY C Potsdam
002851	SUNY CEnv Sci/Frsty
002905	N Carolina A & T
002906	Appalachian State
002923	East Carolina
002950	NC Central U
002972	NC State
002974	North Carolina
002975	UNC Charlotte
002976	UNC Greensboro
002981	Western Carolina
003005	North Dakota
003018	Bowling Green
003032	Cleveland State U
003051	Kent State
003100	Ohio U
003123	Akron
003125	Cincinnati
003131	Toledo
003145	Youngstown State U
003152	Central State U
003154	E Central U
003170	Oklahoma State
003179	Southeastern State
003184	Oklahoma
003210	Oregon State
003216	Portland State
003217	Reed
003218	Chemeketa C
003219	Southern Oregon St C
003223	Oregon
003315	Bloomsburg U of Pa
003316	California U of Pa
003317	Cheyney U of Pa
003320	E Stroudsbrg U of Pa
003321	Edinboro U of Pa
003322	Kutztown U of Pa

003324	Mansfield U of Pa
003325	Millersville U of Pa
003326	Shippensburg U of Pa
003327	Slippery Rock U
003328	West Chester State
003371	Temple
003379	Pittsburgh
003407	Rhode Island C
003414	Rhode Island
003423	Citadel
003425	Clemson
003448	South Carolina
003456	Winthrop
003471	South Dakota State
003474	South Dakota
003478	Austin Peay State
003487	East Tennessee State
003509	Memphis State
003510	Middle Tenn State
003522	Tennessee State U
003523	Tennessee Tech
003529	Chattanooga
003530	Tennessee
003541	Angelo State U
003565	East Texas State
003581	Lamar Tech
003592	Midwestern State U
003594	North Texas State
003599	Pan American U
003606	Sam Houston State U
003615	Southwest Texas St U
003624	Stephen F Austin
003625	Sul Ross State U
003630	Prairie View A&M U
003631	Tarleton State U
003639	Texas A&I U
003642	Texas Southern U
003644	Texas Tech
003646	Texas Women's
003652	Houston
003656	UT Arlington
003658	Texas
003661	UTEP
003665	West Texas State
003675	Utah
003677	Utah State
003696	Vermont
003705	William & Mary
003721	Madison
003728	Old Dominion

003732	Radford
003735	Va Commonwealth
003749	George Mason
003754	Virginia Tech
003764	Virginia State
003765	Norfolk State
003771	Central Washington U
003775	E Washington State
003798	Washington
003800	Washington State
003802	W Washington State
003815	Marshall
003827	West Virginia
003895	Wisconsin
003896	U Wisconsin Milwkee
003915	Stout State
003917	Wisconsin State
003919	UW-Lacrosse
003921	UW Plattevl
003923	UW River Fl
003924	UW Stvns Pt
003925	UW Superior
003926	UW Whitewtr
003932	Wyoming
003935	U of Guam
003944	UPR Mayaguez
003954	U of Central Florida
003955	U of West Florida
003969	Minnesota Twin City
004063	CUNY-Grad School
004509	U Colorado Col Sprgs
004741	Rutgers Camden C
006740	U Colorado Denver
006883	Ohio State
006964	Rutgers
006965	Penn State
006968	Virginia
007022	CUNY Her H Lehman C
007104	Miami (Ohio) Oxford
007108	UPR Rio Piedras
007993	Cal State Bakersfld
008310	Auburn U Montgomery
008810	Indiana U of Pa
009092	Michigan
009145	Governors State U
009168	Wright State U
009235	Clarion U of Pa
009265	N Dakota State U
009333	Sangamon State U
009563	Indiana State U

009630	U Wisconsin Oskosh
009635	Florida Interntl U
009636	Southern U A&M C
009741	U Texas Dallas
009762	U of Southern Maine
009841	U of North Florida
009930	U Texas Permian Basin
010115	U Texas San Antonio
010313	New Mexico
010366	Texas A&M
011161	Corpus Christi St U
011462	U Alaska Anchorage
011711	U Houston Clear Lake
013231	U Houston Victoria
029013	Connecticut
029100	U District of Columbia

Appendix D

Target Institutions

FICE CODE	INSTITUTION
2519	University of Missouri-Saint Louis
1892	University of Iowa
2005	Nicholls State University
1999	University of Louisville
2008	Louisiana Tech University
3639	Texas A & E University
3749	George Mason University
1574	Georgia State University
1976	Morehead State University
3379	University of Pittsburgh Main Campus
1147	California State University-Fresno
3322	Kutztown University of Pennsylvania
1157	California State University-Stanislaus
2188	Salem State College
1950	Wichita State University
1051	The University of Alabama
2551	Kearney State College
3599	Pan American University
2243	Central Michigan University
3581	Lamar University
1977	Murray State University
3032	Cleveland State University
1140	California State University-Los Angeles
1083	University of Arizona
3658	University of Texas At Austin
3896	University of Wisconsin-Milwaukee
2015	University of New Orleans
1372	Western State College of Colorado
3100	Ohio University Main Campus
3656	University of Texas At Arlington
2847	SUNY College At Oneonta
3615	Southwest Texas State University
6740	University of Colorado-Denver
1786	Ball State University
1092	University of Central Arkansas
2653	New Mexico Highlands University
1156	Sonoma State University
2554	University of Nebraska at Omaha
1602	Georgia College
3448	University of South Carolina-Columbia

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